Spatial Implications of Telecommuting in the United States

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A Research Report from the National Center for Sustainable Transportation

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16. Abstract
Telecommuting came roaring to the forefront of the American workplace in the spring of 2020. While no more than 8% of work was done remotely in 2019, shutdowns and social-distancing policies introduced at the onset of the Covid-19 pandemic pushed more than 1 out of every 3 American workers to telecommute. To reflect this shift, the research team aimed to update the spatial modeling toolbox to allow remote employment and develop a quantitative framework capable of analyzing the full range of reallocations, both within and across cities, which may result from its increasing popularity. The researchers build a quantitative spatial model in which some workers can substitute on-site effort with work done from home. The team quantifies their framework to match the distribution of jobs and residents across 4,502 U.S. locations. A permanent increase in the attractiveness of telework results in a rich non-monotonic pattern of reallocations within and across cities. Workers who can telecommute experience welfare gains, and those who cannot suffer losses. Additionally, broader access to jobs reduces inequality across residential locations. The framework robustly predicts changes in residents and housing prices observed 2019—2021.

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EXECUTIVE SUMMARY

In this project, we build a quantitative spatial model in which some workers can substitute on-site effort with work done from home. Ability and propensity to telecommute vary by education and industry. In the model, telecommuting is a choice of a worker that depends on four considerations: (1) commuting time to work, (2) productivity of remote vs on-site work, (3) relative utility of remote work, and (4) the cost of housing relative to the cost of office space. The model nests conventional spatial equilibrium models of commuting; however, the introduction of telecommuting allows studying the consequences of the rise of remote work during the Covid-19 pandemic and beyond.

We document several stylized facts about telecommuting before the pandemic, and ensure that our model is consistent with them. We quantify our framework to match the distribution of jobs and residents across 4,502 U.S. locations. This quantity of locations allows us to capture variation both within and across local labor markets. A permanent increase in the attractiveness of telework results in a rich non-monotonic pattern of reallocations within and across cities. Workers who can telecommute experience welfare gains, and those who cannot suffer losses. Broader access to jobs reduces inequality across residential locations. Our framework robustly predicts changes in residents and housing prices observed 2019--2021.

Our main contribution is to provide a quantitative framework that allows studying effects of spatial policies that account for the ability of workers to work both on-site and from home.

1. Introduction

Telecommuting, once a fond dream of techno-utopians, came roaring to the forefront of the American workplace in the spring of 2020. While no more than 8% of work was done remotely in 2019, shutdowns and social-distancing policies introduced at the onset of the Covid-19 pandemic pushed more than 1 out of every 3 American workers to telecommute. The sudden, enforced prominence of telework, and the surge of experimentation with ways to make it possible, has led many to wonder what role it might play in our future. Surveys indicate that employers plan to allow employees more leeway to work from home after the pandemic than before, with many previously office-bound positions going fully remote.

This matters because the daily commute has been one of the primary sinews stitching commercial and residential areas together within the urban landscape. If this tie is loosened, it seems possible that workers with remote or "hybrid" jobs nominally located in one city center may choose to live beyond the bounds of its conventionally-defined commuting zone—and perhaps on the other side of the country entirely. From a theoretical perspective, either of these outcomes would be impossible in existing conventional models of the urban area, which either focus on a single narrow "commuting zone" and do not allow workers to live outside it, or model the national system of cities under the condition that everyone must live in the same locations as their work.

Therefore, in this paper we aim to update the spatial modeling toolbox to allow re-mote employment, and develop a quantitative framework capable of analyzing the full range of reallocations, both within and across cities, which may result from its increasing popularity. We build a model of location choice and commuting which places no a priori restriction on the location of residence relative to the location of job. We divide the continental United States into 4,502 locations, and allow each worker to freely choose a pair of residence and job sites. Some workers are able to substitute on-site effort with work done from home. Being able to produce output at home saves them from costly commuting, and may induce them to choose a more distant residence location. On the other hand, when working remotely, they have a different level of productivity and have to procure floorspace for a home office. Their choice also depends on a preference shifter which we label *work from home aversion* and which represents tastes, norms, and institutional policies regarding remote work. We show that, because telework allows firms to hire workers from a broader "catchment area," the range of parameter values for which a unique equilibrium is guaranteed is narrower than in a conventional model.

We calibrate our model to be consistent with key facts about pre-2020 telecommuting. Both the opportunity to telecommute, and commuting choices of remote-capable workers, are allowed to differ for college and non-college educated workers, and for workers in tradable and non-tradable industries, consistent with the data. Our framework is also consistent with observed wage differences between remote and on-site workers, the observed distribution of commuting frequencies, and the observed spatial distribution of remote worker residences relative to their employers' job sites.

We calibrate the elasticity of substitution between remote and on-site work, the relative productivity of remote work, and the work from home aversion, separately for each sector and education level. While the values of work from home aversion are similar for all types, the productivity of remote work is higher for the college-educated and for workers in tradable industries, and the elasticity of substitution is lower for those who work in the tradable sector.

We simulate a permanent increase in remote work in the United States by lowering the work from home aversion, and find results which are nuanced and non-monotonic. Workers who can work from home decentralize, ending up much farther from their jobs. Those who cannot work remotely move closer to their workplaces. Around two-thirds of these relocations occur across metro areas, and the remaining one-third within metro areas, underlining the importance of allowing for both types of moves.

Jobs in non-tradable industries follow the mass of residents towards suburbs and small cities. In tradable industries, broader geographic competition for remote workers allows both low-density and the very most central locations to add jobs. Most big cities lose population but those with especially competitive city centers, like New York City, grow. Floorspace prices fall in dense areas and increase in less dense locations. We show that our counterfactual results are a robust predictor of changes in population seen year-over-year between December 2019 and December 2021, both within and across metro areas, as well as of housing rents and prices within metro areas.

We find that income inequality across locations falls, as workers living in a broader set of locations are able to access high-paying jobs in "superstar" cities. Welfare of those who can work from home goes up, as they commute less often and are able to choose location pairs with higher realizations of idiosyncratic preference shocks. Those who cannot work from home do not benefit from these changes, and also face increased competition from remote-capable workers for the highest-paying jobs. As a result, they experience welfare losses. Welfare effects hinge on the extent to which telework contributes to productivity externalities at the workplace. In our baseline scenario, we assume that remote work does not contribute at all. This means that the increase in remote work leads to a decline in average firm productivity. If we assume that remote work contributes fully to these externalities, most of the welfare losses suffered by non-remote workers are canceled.

Our quantitative and disaggregated approach helps us to address a key open question in the remote work literature-was Covid-19 primarily a technology shock affecting remote work productivity, or were changes in tastes, norms, and institutional policies more important?[1] We show that assuming increases in telecommuting are caused solely by an increase in remote work productivity, and not in work from home aversion as in our main counterfactual, leads to implausible wage predictions, which drive population movements that are poorly correlated with the 2019–2021 data. While not conclusive, this evidence suggests that the more important

[1] Barrero, Bloom, and Davis (2021), e.g., promote the primacy of a shift in norms and attitudes, while Davis, Ghent, and Gregory (2022) argue for a shock to productivity.

effect of the Zoompocalypse of 2020 was a shift in norms and attitudes, rather than improvements in productivity.

1.1. Related Literature

Several other recent papers also study the effects of remote work on cities. Behrens, Kichko, and Thisse (2021), Brueckner, Kahn, and Lin (2021), Davis, Ghent, and Gregory (2022), and Kyriakopoulou and Picard (2021) develop stylized spatial equilibrium models with on-site and remote work, and study the implications of greater work from home on the demand for floorspace, productivity, income inequality, and city structure. Relative to these more stylized approaches, our quantitative framework (1) relaxes artificial restrictions on how far away workers can live from their jobs; (2) allows the study of changes not only in residence, but also the location of jobs; (3) allows for, and finds, non-monotonic movements of residents and jobs, in which the smallest cities gain most but the very largest cities decline less, and in some cases, also gain; (4) finds an important role for idiosyncratic location preferences as a motivation for remote worker residence changes. We model telecommuting as an endogenous choice, a feature shared only with Davis, Ghent, and Gregory (2022) from the list above, which allows us to speak to the motivations and contributing factors of the shift towards remote work.

Among quantitative studies of telework, Lennox (2020) builds a quantitative spatial model of Australia and studies a fall in transport costs as a proxy for an increase in remote work. Delventhal, Kwon, and Parkhomenko (2022) build a quantitative spatial model limited to a single urban area—Los Angeles—in which workers are homogeneous and work from home behavior is exogenous.

Monte, Redding, and Rossi-Hansberg (2018) analyze the U.S. system of cities using a model in which workers may commute between counties—an approach which we extend by including many small locations within each urban county to study intra-city, as well as inter-city, adjustments. Also related are recent papers which use models of joint job and residence choice at the city level, such as Ahlfeldt, Redding, Sturm, and Wolf (2015). We contribute to this literature by extending the toolbox to include a full-fledged model of working from home.

Our paper also follows an earlier literature studying the impact of communication technologies and telework, which includes contributions from Gaspar and Glaeser (1998), Ellen and Hempstead (2002), Safirova (2003), Glaeser and Ponzetto (2007), Rhee (2008), and Larson and Zhao (2017).

Yet another strand of recent research empirically studies movement of residents and changes in real estate prices during the pandemic. Examples include Althoff, Eckert, Ganapati, and Walsh (2021), Brueckner, Kahn, and Lin (2021), Haslag and Weagley (2021), Li and Su (2021), Gupta, Peeters, Mittal, and Van Nieuwerburgh (2021), Liu and Su (2021), Rosenthal, Strange, and Urrego (2021), and De Fraja, Matheson, and Rockey (2021), among others.

The remainder of the paper is organized as follows. Section 2 documents key facts about pre-2020 remote work, and presents evidence related to its future trajectory. Section 3 describes the theoretical framework. Section 4 describes the data and the methodology used to quantify the model, and demonstrates how the model is congruent with the facts shown in Section 2. Section 5 presents the results of the counterfactual experiments; tests the predictions of our model against local changes in residents and real estate prices since March 2020; and provides evidence for the preference shock as the driver of the rise in work from home during Covid-19. Section 6 concludes.

2. Remote Work: Past and Present

In this section we establish facts about telecommuting prior to 2020, and present evidence to support our interpretation of Covid-19 as a shock to the preference for remote work. This will motivate the way we build the model as well as how we approach the counterfactual exercise.

Our data is explained in more detail in Appendix A. The data can be accessed at https://doi.org/10.7910/DVN/IJSQEY

2.1. The Who, What and Where of U.S. Telework

In order to construct a sensible model of remote work in the U.S. context, we should first make ourselves familiar with some basic facts. First of all, who can telecommute, and of those, who actually does? Second, what does this telecommuting entail? In particular, how frequently do remote workers work from home, and what are their average wages relative to non-remote workers? Third, where do telecommuters tend to live?

To address the first question, we subdivide the work force by education level and by industry. College workers have obtained a four-year degree or more, and non-college have not. Tradable industries are 2-digit NAICS categories whose products are often sold far from the location of origin, while non-tradable industries are categories whose products are mostly sold locally.[2] Using data on full-time workers in the 48 contiguous United States and Washington, D.C. from the American Community Survey (ACS), we calculate that the U.S. workforce between 2012–2016 was composed of 28.9% college workers, 12.3% in tradable and 16.6% in non-tradable industries; and 71.1% non-college workers, 28.8% in tradable and 42.3% in non-tradable industries.

Telecommutability, i.e., the ability to telecommute, differs sharply between these categories. Combining occupational classifications from Dingel and Neiman (2020) with our data, we find that 33.6% of workers in our sample have jobs that can be done from home. We also find that college workers and those in tradable industries are more likely to have such a job—an observation we label **Stylized Fact #1**. As shown in Figure 1, 68.8% of college workers in

[2] We use the BEA 2012 NAICS categories and divide them as follows. *Tradable:* Agriculture, forestry, fishing and hunting, and mining; Manufacturing; Wholesale trade; Transportation and warehousing, and utilities; Information; Finance, insurance, real estate and rental and leasing; and Professional, scientific, management, administrative, and waste management services. *Non-tradable:* Educational, health and social services; Arts, entertainment, recreation, accommodation and food services; Other services (except public administration); and Public administration. Excluded: Armed Forces.

tradable industries have jobs that can be done mostly or completely from home, compared to just 18.9% of non-college workers in non-tradable industries.[3]

These differences are compounded by further gaps in telecommuting uptake. To measure uptake, we use data from the 2018 Survey of Income and Program Participation (SIPP); see Appendix Section A.1 for more details. Focusing on full-time workers who are not self-employed, we find that 38% of college workers in tradable industry with telecommutable occupations actually do work from home at least one full paid day a week; while uptake for non-college, non-tradable workers is only 21%.[4] We dub these gaps by education and industry **Stylized Fact #2**.

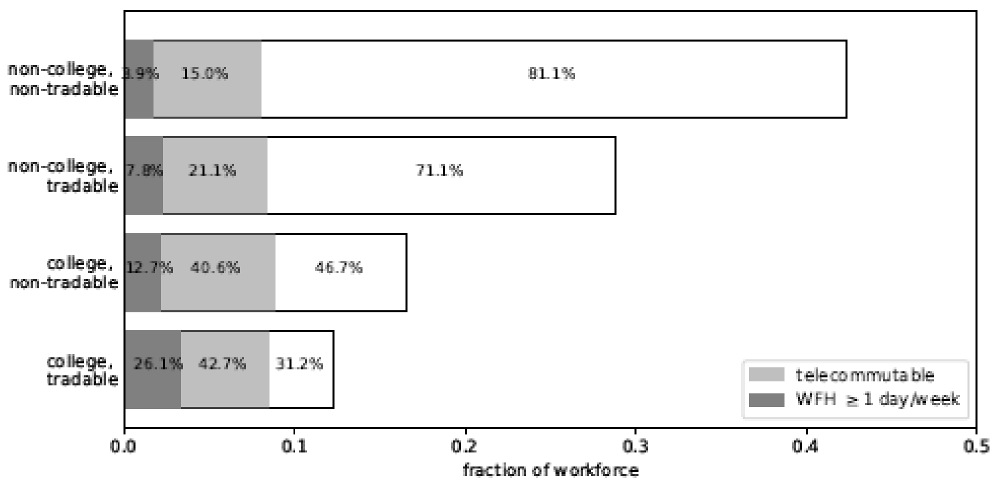

Figure 1. Telecommutability and uptake

Note: Total bar length corresponds to the share of each worker type in the labor force. Dark-gray areas represent workers who report at least one paid full day/week worked from home. Light-gray areas represent workers with telecommutable professions who do not work from home. White areas represent workers in non-telecommutable occupations. Percentages on the graph report the fraction of each worker type with each commuting status.

With what frequency do remote workers dial it in from home? Table 1 provides an answer. Using the data from SIPP, we find that a notable feature of the distribution for each worker category is bi-modality: most are full-time on-site or full-time at home, with few workers in between. We call this **Stylized Fact #3**.[5]

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[3] Differences in telecommutability by industry and education have been previously documented by Dingel and Neiman (2020) and Mongey, Pilossoph, and Weinberg (2020).

[4] We calculate $26.1/(26.1 + 42.7) \approx 0.38, and\ 3.9/(3.9 + 15.0)0.21$, from Figure 1.

[5] An advantage of the SIPP data is that it allows us to calculate numbers for each frequency from a single data source applying a consistent methodology. Mas and Pallais (2020) also reports some numbers related to work from home frequency, but the variance in definitions across the patchwork of data sources obscures the bimodality that we find here. Another advantage of SIPP is that the sample sizes are large enough for us to focus on full-time workers, and that it counts full paid days worked from home. The 2017 Leave and Job Flexibility module of the American Time Use Survey has smaller sample size and counts any day when the majority of work was done from home, regardless of whether that work was paid or not, and regardless of whether it was a full day or just an hour or two. We believe that these differences are why this survey reports somewhat different patterns, which can be

Table 1. Frequencies of working from home, 2018

WFH Frequency	Overall	College		Non-college	
		Tradable	Non-Tradable	Tradable	Non-Tradable
5 days per week	5.6%	15.0%	6.7%	5.2%	2.7%
4 days per week	0.2%	0.5%	0.5%	0.2%	0.1%
3 days per week	0.3%	0.9%	0.4%	0.3%	0.1%
2 days per week	0.7%	1.9%	1.4%	0.5%	0.3%
1 day per week	2.3%	7.8%	3.7%	1.6%	0.7%
<1 day per week	90.8%	73.9%	87.3%	92.3%	96.2%

Note: The table summarizes the share of all workers, as well as workers in each education-industry group, that report having a certain number of paid full days a week worked from home from SIPP. Self-employed workers are excluded.

How do the earnings of telecommuters compare to those who work full-time in the office? To answer this question, we estimated hourly earnings controlling for age, sex, race, industry, occupation, and the public-use microdata area (PUMA) of residence separately for workers who belong to a telecommutable occupation but report working full time on site and workers who work full time from home. In Table 2 we report that at least from 2012–2016, remote workers did not appear to earn any less on average than their counterparts who belonged to a telecommutable occupation but worked on-site full time; see Appendix Section A.2 for more details on the data. On the contrary, for every category except for non-college workers in non-tradable industries, we observe a modest work from home wage premium. We call this **Stylized Fact #4**.[6]

Table 2. Relative earnings of telecommuters

	Non-college	College
Non-tradable	-1.5%	+2.4%
Tradable	+2.6%	+5.2%

Note: Hourly earnings of those who entirely worked from home last week, versus those who did not. ACS 2012-2016, only for workers in telecommutable occupations, controlling for age, sex, race, industry, occupation, and geographical location using a linear regression.

Finally, does the ability to telecommute affect workers' location choices? Using data from the 2017 National Household Transportation Survey (NHTS), we find a positive relationship between work-from-home frequency and distance to job site, as shown in Figure 2; see

seen, for example, in Table 3 of the related Bureau of Labor Statistics news release: (https://www.bls.gov/news.release/flex2.t03.htm#cps_jf_table3.f.1).

[6] This does not necessarily mean that working from home is more productive. The observed premium is consistent with a wide variety of causes, including unobserved differences between remote and non-remote workers, and a possible work-from-home productivity bonus. Survey evidence from Barrero, Bloom, and Davis (2021) provides some support for the latter possibility. They find that workers forced to work from home during 2020–2021 reported a nearly 8% increase in productivity on average.

Appendix Section A.4 for more details on the data.[7] We shall refer to this relationship as **Stylized Fact #5**. It is consistent with telework being a way of reducing the effective commuting cost.

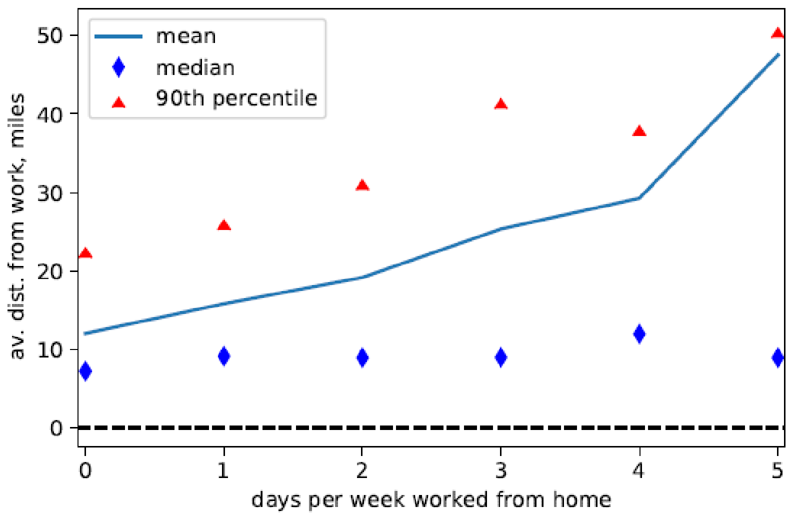

Figure 2. Telecommute frequency versus distance to workplace

Note: Calculated from NHTS. 5 days/week: worked from home more than 90% of the days in a 21.67 day average work month; 4 days: between 90% and 70%, 3 days: between 70% and 50%, etc.

2.2. Covid-19: A Telework Shock

When the Covid-19 pandemic began in early 2020, lockdowns and distancing policies moved over one-third of the U.S. workforce from offices to their homes. Prior to the pandemic, no more than 8% of paid full workdays were remote.[8] By early May 2020, 35% of workers who commuted daily before Covid-19 switched to working remotely (Brynjolfsson, Horton, Ozimek, Rock, Sharma, and TuYe, 2020).

[7] Zhu (2012) also found that telecommuters live at a farther distance from work than commuters.

[8] Based on 2018 SIPP data. This is in the upper range of numbers in Mas and Pallais (2020).

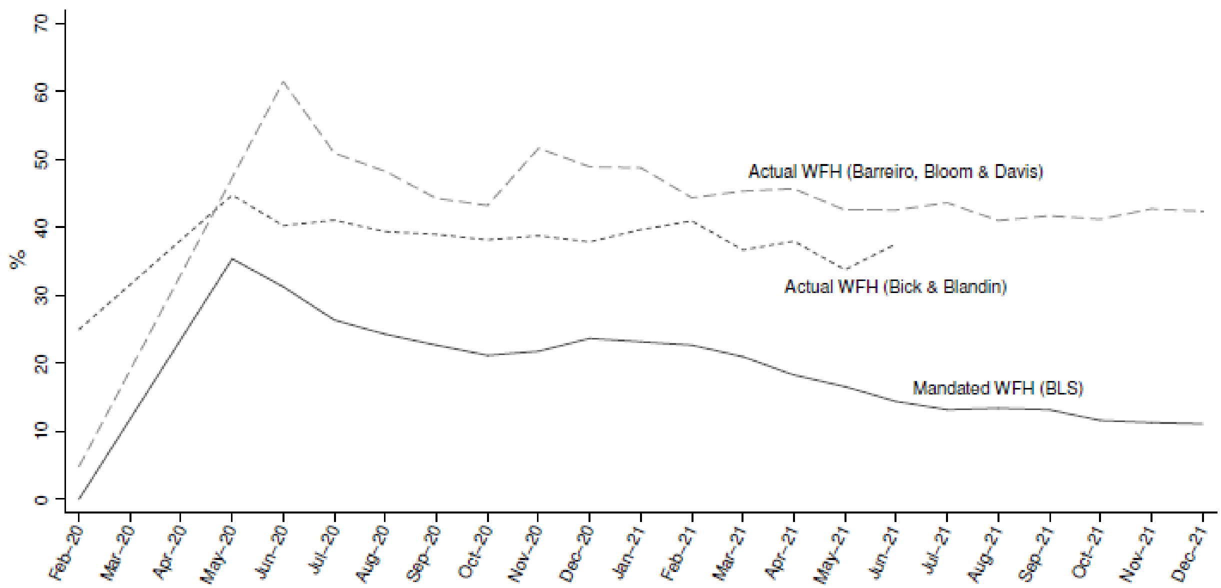

Figure 3. Work from home during the Covid-19 pandemic

This sudden upheaval sparked consternation in many but, in survey after survey of workers and managers, an interesting pattern emerged. It was all going rather better than almost anyone had expected. Companies and workers had found ways to adjust without losing too much productivity, and many found a lot to like about remote work. So much so, that surveys by Barrero, Bloom, and Davis (2021) suggest a full 22% of paid workdays will be remote even after the pandemic.[9]

There are at least four hypotheses as to what the Covid-19 telework shock really was. None are mutually exclusive, though some may be more important than others. And the implications of each for the future of remote work are quite distinct.

First, there is the view that working from home during the pandemic is a purely transitory phenomenon, and that once people are allowed to and feel safe they will flock straight back to the office. Second, there is the view that we have experienced a shock to preferences around working from home. Barrero, Bloom, and Davis (2021) take the position that working from home was always great but social norms and stigma limited it. They also document a positive change in attitude by the average worker towards telework after having actual experience with working from home. Third, events of the past two years may amount to a technology shock. The early months after March 2020 saw a burst of innovation directed at making remote work, work. New software was developed and widely adopted, new policies and procedures were put in place, sizable investments in remote-complementary physical capital were made, and individuals and organizations did a great deal of learning by doing. Fourth, it could be that work

[9] Other surveys indicate that remote work will be more common post-pandemic: Bartik, Cullen, Glaeser, Luca, and Stanton (2020), Ozimek (2020), Bick, Blandin, and Mertens (2021), inter alia.

mode is a coordination game with multiple equilibria—if everyone is in the office, workers want to be there, but if enough people go remote, workers prefer to stay home.

The first hypothesis does not seem to be supported by the trends shown in Figure 3. The share of mandated remote work has fallen from 35% in May 2020 to 11% by the end of 2021. Over the same period, two measures of *actual* working from home—Bick and Blandin's and Barrero, Bloom, and Davis's—have remained roughly constant at around 40%. We therefore believe it is highly likely that some combination the latter three hypotheses are playing a role. In Section 5, we will present evidence that a *preference shock* is more plausible as a primary explanation for changes in work-from-home behavior than a *technology shock*. We leave the possible role of workplace coordination as a potential topic of future research.

3. Model

Consider a national economy which consists of a finite set $\mathcal{J}$ of discrete locations. Each location is populated by a continuous measure of workers who are distinguished by two characteristics. First, each worker has a skill-level $s \in \{H, L\}$. College-educated workers $(s = H)$ provide High-skilled labor to employers, and non-college-educated workers $(s = L)$ provide Low-skilled labor. Second, a worker belongs to one of two types of occupations, $o \in \{T, N\}$ Some occupations are Telecommutable $(o = T)$, i.e., amenable to remote work, while other occupations are Non-telecommutable $(o = N)$and must be performed on-site.[10] The four types that are the product of $\{H, L\}$ and $\{T, N\}$ are taken to be exogenous and immutable. The economy-wide fraction of workers with education s and occupation o is denoted by l^{so}. Total employment of all types of workers is fixed and normalized to one, so that $l^{HN} + l^{LN} + l^{HT} + l^{LT} = 1$.

Three types of output are produced in each location: tradable goods and services, non-tradable goods and services, and floorspace, $m \in \{G, S, F\}$. Tradable output $(m = G)$ is produced by combining college- and non-college labor with floorspace, and may be sold in any other location without paying a shipping cost. Non-tradable output $(m = S)$ is produced using the same three inputs, but can only be sold in the location of origin.[11] Floorspace $(m = F)$ is produced by combining land with tradable goods, and may only be used in the same location it is built.

Work at home is modeled as an option of telecommutable workers to split their work time between their job site and their residence. The productivity of at-home work relative to on-site work, the elasticity of substitution between the two work modes, as well as a preference parameter that we call the aversion to work from home vary across education levels and industries. A worker chooses to spend more time working at home when remote work is

[10] Examples of telecommutable occupations are architects and call center representatives. Examples of non-telecommutable occupations include dentists and plumbers

[11] Tradable output is indexed $m = G$ as in our data it consists largely (though not entirely) of Goods, while non-tradable is indexed $m = S$ for Services, for the same reason.

relatively productive, the aversion to it is relatively low, floorspace at home is relatively cheap, and the commute to the job site is long.

3.1. Workers

All workers make three types of choices. First, they choose which industry to work in; second, the locations of their job and their residence; and third, how to divide their resulting disposable income between spending on tradables, non-tradables and housing. Those belonging to telecommutable professions make one additional decision after choosing industry, job and residence location: how to divide their labor time between working in the office and working at home. The first three types of choices are not unusual in a quantitative spatial model and are discussed immediately below. The choice of how often to work from home is described later in Section 3.1.1.

Consumption preferences are Cobb-Douglas. Optimal consumption choices for individual worker of education level s and occupation o, conditional on a choice of location i as a residence, j as a worksite, and a choice of m as an industry, imply the indirect utility of

$$\mu_{m,l}\xi_{ij,l}v_{mij}^{\mathrm{s}}(\theta)$$

Here $\theta \in [0,1]$ is the fraction of time worked on-site, for the moment left undetermined; $\mu_{m,l}$ represents idiosyncratic preferences over industry, drawn from a Fréchet distribution $\Phi_{\text{ind}}(\mu) = \exp(-\mu^{-\sigma})$; and $\xi_{ij,l}$; represents idiosyncratic preferences over residence-workplace pairs, also drawn from a Fréchet distribution $\Phi_{\text{loc}}(\xi) = \exp(-\xi^{-\sigma})$; The common component of indirect utility is

$$v_{mij}^{so}(\theta) \equiv \frac{X_{mi}^{s}E_{mj}^{s}}{p_i^{\beta}q_i^{\gamma}}\frac{\tilde{w}_{mij}^{so}(\theta)}{d_{ij}(\theta)g_{ij}} \tag{3.1}$$

In this expression, p_i is the price of non-tradables, q_i is the price of floorspace, and $\beta, \gamma \in (0,1)$ are the expenditure shares of these two categories. X_{mi}^{s} is a residential amenity and E_{mj}^{s} is an employment amenity. Disposable income $\tilde{w}_{mij}^{so}$ depends on θ in a way which we will discuss later in this section. The disutility of commuting $d_{ij}^{so}(\theta)$ also depends on θ and is given by

$$d_{mij}^{SO}(\theta) \equiv \theta e^{\kappa t_{ij}} + (1-\theta)\varsigma_m^{S} \tag{3.2}$$

where t_{ij} is the time in minutes required to commute from location i to j; $\kappa > 0$ is the elasticity of the disutility to commute time; and $\varsigma_m^{S} > 0$ represents the relative preference of an s-educated worker in industry m to work in the office, as opposed to at home.

In what follows, we will refer to ς_m^{S} as the “aversion to telecommuting.” Assuming that ς_m^{S} takes a value greater than 1 (as it does for all worker categories in our calibration), it lends itself to a range of interpretations, not all of which fall within the realm of worker “preferences” or average tastes per se. For example, they could also reflect worker concerns about career advancement, which may be easier to achieve in the office; or restrictions against work-from-home imposed by convention, or bias, or employer regulations.

The worker only experiences the part of disutility which comes from commuting on the days she commutes: the first term of equation (3.2) ranges from 0 when $\theta = 0$, to $e^{\kappa t_{ij}}$ when $\theta = 1$. The second term, representing disutility from remote work, has the opposite relationship with θ, ranging from 0 when $\theta = 1$ to ς_m^S when $\theta = 0$.

We also allow for reasons not directly related to commuting to cause workers to prefer shorter commutes between work and home.[12] We represent these with the distance penalty $g_{ij} \equiv e^{\tau t_{ij}}$, with $\tau > 0$ determining the strength of distance dependence.[13] This dependence is necessary for model predictions to conform with the distance-commute frequency relationship reported in Section 2: even workers who rarely come to the office tend to live at commutable distances from their job site. In Appendix Section I.1 we recalibrate the benchmark model and repeat our main counterfactual exercise assuming that $g_{ij} = 1$ so the whole cost of distance is loaded onto commuting.

Let us designate the optimal choice of θ, discussed later, as θ_{muj}^{so}; and the associated indirect utility, disposable income, and disutility of commuting as v_{muj}^{so}, $\widetilde{w}_{muj}^{so}$, and d_{muj}^{so}. Given indirect utilities characterized by equation (3.1), and the Fréchet distribution of shocks, it is straightforward to show that the measure of workers of education level s and occupation o who choose industry m, residence i and job site j is given by

$$\pi_{mij}^{so} = l^{so}\pi_m^{so}\pi_{ij|m'}^{so} \tag{3.3}$$

where π_m^{so} is the probability that a worker with education level s and occupation o chooses industry m, and $\pi_{mij}^{so}$is the probability that such a worker chooses the location pair $(i;\ j)$, conditional on having chosen industry m. These two probabilities are given by

$$\pi_m^{so} = \frac{\left[\sum_i \sum_j \left(v_{mij}^{so}\right)^{\epsilon}\right]^{\frac{\sigma}{\epsilon}}}{\sum_{m'}\left[\sum_i \sum_j \left(v_{m'ij}^{so}\right)^{\epsilon}\right]^{\frac{\sigma}{\epsilon}}} \text{ and } \pi_{ij|m}^{so} = \frac{\left(v_{mij}^{so}\right)^{\epsilon}}{\sum_{i'}\sum_{j'}\left(v_{mi'j'}^{so}\right)^{\epsilon}} \tag{3.4}$$

Choice probabilities π_{mij}^{so} allow us to characterize aggregate allocations of residents and jobs. For example, the residential population (indexed by R) of type (s, o) workers in location i is

$$N_{Ri}^{so} = \sum_m \sum_j \pi_{mij}^{so} \tag{3.5}$$

Also, the supply of on-site work days (indexed by WC) by workers of skill level s at job site j and the supply of remote work days (indexed by WT) are given by

$$N_{WCj}^{s} = \sum_m \sum_i \left[\theta_{mij}^{sT}\pi_{mij}^{sT} + \pi_{mij}^{sN}\right] \text{ and } N_{WTj}^{s} = \sum_m \sum_i \left(1 - \theta_{mij}^{sT}\right)\pi_{mij}^{sT} \tag{3.6}$$

[12] We see three possible interpretations: (1) Spatial frictions in the process of finding jobs and forming attachments to residential locations, leading to spatial covariance in idiosyncratic preferences. (2) Employees with longer tenure on-site, who have already established residential attachments nearby, may be more likely to begin remote work. (3) Company policies may discourage moving far away, perhaps due to the option value of occasional office visits.
[13] An alternative specification could embed this distance penalty in the distribution of preference shocks, so that workers are less likely to draw a shock with high value for a pair of distant locations.

Finally, the expected utility (and our measure of welfare) of a worker with education s and occupation o is

$$V^{so} = \Gamma\left(\frac{\epsilon-1}{\epsilon}\right)\Gamma\left(\frac{\sigma-1}{\sigma}\right)\left[\sum_m\left[\sum_i\sum_j\left(v_{mij}^{so}\right)^{\epsilon}\right]^{\frac{\sigma}{c}}\right]^{\frac{1}{\sigma}}, \tag{3.7}$$

where $\Gamma(.)$ is the Gamma function.

3.1.1. Allocation of Time Between On-Site and Remote Work

Workers supply one unit of work time inelastically. This is a common assumption. What is different in our model is that some workers—those in telecommutable occupations—choose how to divide their work time between the job site and home. In a given work location, whether on-site or at home, labor time n is combined with floorspace h in a Cobb-Douglas production function to produce effective labor: $n^{\alpha}h^{1-\alpha}$.[14]

We assume that tasks done at home are different from those done at the job site. Reflecting this, overall effective labor supply of a worker is a constant elasticity of substitution combination of labor on-site and at home, with the elasticity of substitution for each education level and industry $\varsigma_m^S > 1$:[15]

$$z_m^{so}(\theta, h_C, h_T) = \left[\left(\theta^{\alpha}h_{WC}^{1-\alpha}\right)^{\frac{\varsigma_m^S-1}{\varsigma_m^S}} + \left(v_m^s(1-\theta)^{\alpha}h_{WT}^{1-\alpha}\right)^{\frac{\varsigma_m^S-1}{\varsigma_m^S}}\right]^{\frac{\varsigma_m^S}{\varsigma_m^S-1}}. \tag{3.8}$$

Parameter $v_m^s > 0$ is the relative productivity of working from home. It represents all possible reasons why a given worker may produce a different quantity of output while working at home, such as a different work environment, lack of supervision, or the difficulty of coordinating with co-workers. Variables h_{WC} and h_{WT} are the amounts of on-site and home floorspace, respectively, rented by the worker.[16] A worker of education level s in industry m takes as given that they will be paid a wage w_{mj}^s for each unit of effective labor they supply to their employer. Thus, the worker's disposable income is the compensation paid by the firm less floorspace expenses,

$$\tilde{w}_{mij}^{so}(\theta) \equiv w_{mj}^5 z_m^s(\theta, h_{Wc}, h_{WT}) - q_j h_{WC} - q_i h_{WT}.$$

[14] The need to use floorspace to produce output from home is consistent with Stanton and Tiwari's (2021) finding that, conditional on location, income, and family structure, telecommuters own larger houses.

[15] Imperfect substitution between on-site and remote work implies that all workers in telecommutable occupations choose an interior θ.

[16] For simplicity of exposition, we specify floorspace rent as a choice by the worker; firms' payments to workers compensate both labor and floorspace. There exists an isomorphic specification in which firms rent floorspace directly

Income-maximizing choices imply the following floorspace expenditures of a worker with education s in occupation o who lives in location i, works in industry m in location j, and commutes to the job site a fraction θ of time:

$$q_j h^{so}_{mij,WC}(\theta) = \left((1-\alpha)w^{5}_{mj}\right)^{\frac{1}{\alpha}}\left[\left(\theta^{\alpha} q_j^{-(1-\alpha)}\right)^{\varsigma^s_m - 1}\Omega^{s}_{mij}(\theta)\right]^{\frac{1}{1+\alpha(\varsigma^s_m - 1)}} \tag{3.9}$$

$$q_i h^{so}_{mij,WT}(\theta) = \left((1-\alpha)w^{s}_{mj}\right)^{\frac{1}{\alpha}}\left[\left(v^s_m(1-\theta)^{\alpha} q_i^{-(1-\alpha)}\right)^{\varsigma^s_m - 1}\Omega^{s}_{mij}(\theta)\right]^{\frac{1}{1+\alpha(\varsigma^s_m - 1)}} \tag{3.10}$$

where

$$\Omega^{so}_{mij}(\theta) \equiv \left[\left(\theta^{\alpha} q_j^{-(1-\alpha)}\right)^{\frac{\varsigma^s_m - 1}{1+\alpha(\varsigma^s_m - 1)}} + \left(v^s_m(1-\theta)^{\alpha} q_i^{-(1-\alpha)}\right)^{\frac{\varsigma^s_m - 1}{1+\alpha(\varsigma^s_m - 1)}}\right]^{\frac{1}{\alpha}\frac{1+\alpha(\varsigma^s_m - 1)}{\varsigma^s_m - 1}}. \tag{3.11}$$

Then the optimal effective labor of a worker who rents optimal amounts of floorspace and commutes to work with frequency θ is $z^{so}_{mij}(\theta) = \left((1-\alpha)w^{5}_{mj}\right)^{\frac{1-a}{\alpha}}\Omega^{so}_{mij}(\theta)$ while his disposable income is

$$\widetilde{w}^{so}_{mij}(\theta) = \alpha(1-\alpha)^{\frac{1-a}{a}}\left(w^{s}_{mj}\right)^{\frac{1}{a}}\Omega^{so}_{mij}(\theta) \tag{3.12}$$

Finally, in order to choose how much time to work on-site and at home, a telecommutable worker compares the benefits and costs of working on-site. Maximizing (3.12) with respect to θ, we obtain

$$\theta^{sT}_{mij} = \left[1 + \left(v^s_m\left(\frac{q_j}{q_i}\right)^{1-\alpha}\right)^{\varsigma^s_m - 1}\left(\frac{e^{xt_{ij}}}{\varsigma^0_m}\right)^{1+\alpha(\varsigma^s_m - 1)}\right]^{-1}. \tag{3.13}$$

Thus, a worker will choose to work from home more often, i.e., choose lower θ, when telework is relatively productive (large v^s_m), floorspace at home is relatively cheap (large q_j/q_i) the aversion to work from home is low (small ς^s_m), and the commuting cost is high (large t_{ij}).

3.2. Firms

In each location there are many perfectly competitive firms producing tradable products, and likewise producing non-tradable products. A firm in industry m and location j produces output

$$Y_{mj} = A_{mj}\left[\omega_{mj}\left(y^L_{mj}\right)^{\frac{\xi-1}{\xi}} + \left(1-\omega_{mj}\right)\left(y^H_{mj}\right)^{\frac{\xi-1}{\xi}}\right]^{\frac{\xi}{\xi-1}} \tag{3.14}$$

where y^s_{mj} represents the total effective labor rented from workers with education s, ω_{mj} determines the weight of non-college labor in the production function, $A_{mj\mathrm{j}}$ is the productivity of industry m in location j, and ξ is the elasticity of substitution between college and non-college labor. In our setup, the decision of how to divide labor time between on-site and at-home work is made by the worker, and the firm is ready to purchase however much effective labor results from the worker's choices.

The firm chooses labor inputs y_{mj}^{S} so as to maximize profit: $p_{mj}Y_{mj} - w_{mj}^{L}y_{mj}^{L} - w_{mj}^{H}y_{mj}^{H}$: Profit maximization implies the following equilibrium relationship between non-college wages and output prices in each industry,

$$\frac{w_{mj}^{L}}{p_{mj}} = A_{mj}\omega_{mj}^{\frac{\xi}{\xi-1}}\left[1 + \left(\frac{1-\omega_{mj}}{\omega_{mj}}\right)^{\xi}\left(\frac{w_{mj}^{L}}{w_{mj}^{H}}\right)^{\xi-1}\right]^{\frac{1}{\xi-1}} \tag{3.15}$$

Since there are no transport costs for shipping the output of the tradable sector, there is an economy-wide price for tradable products, normalized to 1: $p_{Gj} = 1$ for all j. Firms in the non-tradable sector can only sell their product locally and thus $p_{Sj} = ph$ varies by location. Meanwhile, optimal use of inputs implies that in each industry m and each location j, the college premium has the following relationship to the relative input level of each skill type:

$$\frac{w_{mj}^{H}}{w_{mj}^{L}} = \frac{1-\omega_{mj}}{\omega_{mj}}\left(\frac{y_{mj}^{L}}{y_{mj}^{H}}\right)^{\frac{1}{\xi}} \tag{3.16}$$

3.3. Developers

Floorspace is demanded by workers both for residential use and as a production input. In each location, there is a large number of perfectly competitive developers which produce floorspace using technology

$$H_i = K_i^{1-\eta_i}(\phi_i L_i)^{\eta_i}, \tag{3.17}$$

where K_i and L_i are the inputs of the tradable good and land, and η_i is the location-specific share of land in the production function. We make a simplifying assumption that the production of floorspace does not employ labor directly. Each location is endowed with Λ_i units of buildable land which serves as the upper bound on the developers' choice of land: $L_i \leq \Lambda_i$. Parameter ϕ_i stands for the local land-augmenting productivity of floorspace developers.[17] Let q_i be the equilibrium price of floorspace. Then the equilibrium supply of floorspace in location i is

$$H_i = \phi_i(1-\eta_i)^{\frac{1-\eta_i}{\eta_i}} q_i^{\frac{1-\eta_i}{\eta_i}} L_i. \tag{3.18}$$

[17] The productivity may depend on terrain, climate, land use regulations, etc.

3.4. Market Clearing

There are five markets that need to clear in each location in an equilibrium: the market for college labor, the market for non-college labor, the market for non-tradable output, the market for floorspace, and the market for land.[18]

Labor markets clear when the demand for effective labor of each education level equals the supply, $y_{mj}^{s} = \sum_{o}\sum_{i}\pi_{mij}^{so} z_{mij}^{so}$, which implies that equilibrium effective labor supply is

$$y_{mj}^{s} = \left((1-\alpha)w_{mj}^{s}\right)^{\frac{1-\alpha}{\alpha}} \sum_{0}\sum_{i}\pi_{mij}^{so}\Omega_{mij}^{so} \tag{3.19}$$

Applying equation (3.19) to equation (3.16), we obtain the equilibrium college wage premium,

$$\frac{w_{mj}^{H}}{w_{mj}^{L}} = \left(\frac{1-\omega_{mj}}{\omega_{mj}}\right)^{\frac{\alpha\xi}{1+\alpha(\xi-1)}} \left(\frac{\sum_{0}\sum_{i}\pi_{mij}^{Lo}\Omega_{mij}^{Lo}}{\sum_{0}\sum_{i}\pi_{mij}^{Ho}\Omega_{mij}^{Ho}}\right)^{\frac{\alpha}{1+\alpha(\xi-1)}} \tag{3.20}$$

Wage levels can then be found by plugging in this expression in equation (3.15).

Profit-maximization and zero profits imply the following equilibrium supply of the non-tradable product in location j,

$$p_{Sj}Y_{Sj} = \left(p_{Sj}A_{Sj}\right)^{\frac{1}{\alpha}}(1-\alpha)^{\frac{1-\alpha}{\alpha}}\omega_{Sj}^{\frac{\varepsilon}{(\xi--1)}}\left(\sum_{0}\sum_{i}\pi_{Sij}^{Lo}\Omega_{Sij}^{Lo}\right)\left[1+\left(\frac{1-\omega_{Sj}}{\omega_{Sj}}\right)^{\varepsilon}\left(\frac{w_{Sj}^{L}}{w_{Sj}^{H}}\right)^{\varepsilon-1}\right]^{\frac{1+\alpha(\xi-1)}{\alpha(\xi-1)}} \tag{3.21}$$

Let total disposable income in residential location i be $W_i \equiv \Sigma_s\Sigma_0\Sigma_m\Sigma_j\pi_{mij}^{s0}\widetilde{w}_{mij}^{so}$. Non-tradables are demanded only by workers for consumption and total spending on the non-tradable output in any residential location i is βW_i. This allows us to construct the following market-clearing condition in the market for non-tradables:

$$p_{Sj}A_{Sj} = \frac{(\beta W_i)^{\alpha}}{(1-\alpha)^{1-\alpha}\omega_{Sj}^{\frac{\xi}{\xi-1}}\left(\sum_{o}\sum_{i}\pi_{Sij}^{Lo}\Omega_{Sij}^{Lo}\right)^{\alpha}}\left[1+\left(\frac{1-\omega_{Sj}}{\omega_{Sj}}\right)^{\xi}\left(\frac{w_{Sj}^{L}}{w_{Sj}^{H}}\right)^{\xi-1}\right]^{-\frac{1+\alpha(\xi-\xi-1)}{\alpha(\xi-1)}} \tag{3.22}$$

Demand for residential floorspace in location i is $H_{Ri} = \gamma W_i/q_i$. Demand for on-site office space is $H_{WCi} = \sum_s\sum_o\sum_m\sum_j \pi_{mji}^{so}h_{mji,WC}^{so}$, and demand for home office space is $H_{WTi} = \sum_s\sum_m\sum_j \pi_{mij}^{sT}h_{mij,WT}^{sT}$. Then, total local floorspace demand is

$$H_i = H_{Ri} + H_{WCi} + H_{WTi}. \tag{3.23}$$

Floorspace demand also determines the demand for land. Land is owned by landlords and, since there are no alternative uses of land, it is optimal for landlords to sell all buildable land to developers: $L_i = \Lambda_i$ for all i. Land owners receive a share η_i of the total revenues from

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[18] By Walras' Law, the economy-wide market for tradables clears as long as the other I 5 local markets clear.

floorspace sales, $q_i H_i$. The price per unit of land must then be equal to total earnings divided by the quantity of land:

$$l_i = \frac{\eta_i q_i H_i}{\Lambda_i}. \tag{3.24}$$

Landlords use proceeds from land sales to consume the tradable good only, as in [?]. Thus, the welfare of landlords is simply the total value of land in the economy, $\sum_i l_i \Lambda_i$. Finally, optimal decisions of developers imply the following relationship between land prices and floorspace prices:

$$q_i = \frac{1}{\eta_i^{\eta_i}(1-\eta_i)^{1-\eta_i}} \left(\frac{l_i}{\phi_i}\right)^{\eta_i}. \tag{3.25}$$

3.5. Externalities

The productivity of industry m in location j is determined by an exogenous component, a_{mj}, and an endogenous component that is increasing in the local density of on-site and remote employment:

$$A_{mj} = a_{mj} \left(\frac{N_{WCj} + \psi N_{WTj}}{\Lambda_j}\right)^{\lambda}. \tag{3.26}$$

Parameter $\lambda > 0$ is the elasticity of productivity with respect to employment density, and $\psi \in [0,1]$ is the degree of remote workers' participation in productive externalities. These externalities include learning, knowledge spillovers, and networking that occur as a result of face-to-face interactions between workers. When workers are working from home, they may not participate fully in interactions that give rise to these externalities. As we will see, the value of ψ has important consequences for welfare effects of telecommuting.

Similarly, the residential amenity in location i is determined by an exogenous component, x_{mi}^s, and an endogenous component that depends on the density of residents:

$$X_{mi}^s = x_{mi}^s \left(\frac{N_{Ri}}{\Lambda_i}\right)^{\chi}, \tag{3.27}$$

where $\chi > 0$ is the elasticity of amenities with respect to the local density of residents.[19] The positive relationship between residential density and amenities represents in reduced form the greater propensity for amenities, such as parks or schools, to locate in proximity to greater concentrations of potential users.[20]

[19] We abstract from spatial spillovers of productivity or amenities across locations. They are highly localized, as found in Ahlfeldt, Redding, Sturm, and Wolf (2015). and other studies. Given that locations in our quantitative model are relatively large, the effect of these spillovers may not be first-order.

[20] We assume that all workers contribute equally to amenity externalities at their location of residence. It is also possible that those who work at home more often contribute more to local amenities by spending more time in the area of their residence.

3.6. Equilibrium

Given local fundamentals, a_{mj}, x^s_{mi}, E^s_{mj}, ϕ_i, η_i, and Λ_i; bilateral commute times, t_{ij}; population shares, I^{so}; and economy-wide parameters, ν^s_m, ς^s_m, I^{so}, ψ, α, β, γ, ϵ, σ, ζ^s_m, ξ, κ, τ, λ, and χ; a *spatial equilibrium* consists of allocations of workers to industries, residences, and job-sites, π^{so}_{mij}; allocations of work time between on-site and remote, θ^{so}_{mij}; productivities, A_{mj}; residential amenities, X^s_{mj}; college and non-college wages, w^H_{mj} and w^L_{mj}; effective labor supplies, y^s_{mj}; prices and supplies of floorspace, q_i and H_i; prices and supplies of non-tradable goods, p_i and Y_{Si}; and land prices, l_i; such that equations (3.3), (3.13), (3.26), (3.27), (3.15), (3.20), (3.19), (3.25), (3.18), (3.22), (3.21), and (3.24) are satisfied.

3.6.1. Existence and Uniqueness

While our model has a number of extensions compared to a "standard" quantitative spatial equilibrium model with commuting such as Ahlfeldt, Redding, Sturm, and Wolf (2015), our main innovation is the introduction of work from home. In Appendix Section B, we evaluate equilibrium properties of a simplified model with exogenous floorspace supply, single industry, and no heterogeneity in education or occupation, but with work from home. We show that, in general, the introduction of telecommuting narrows the range of parameter values for which a unique equilibrium is guaranteed. In a standard model, the extent to which a location with high exogenous productivity attracts employment is amplified via agglomeration externalities but is dampened as the number of workers willing to commute to this location daily is limited. In a model with work from home, such locations have a greater firm market access to potential workers (or "catchment area") because they do not have to commute daily. As a result, even modest values of the productive externality parameter λ can lead to multiple equilibria.

4. Quantification

In this section we describe how we build our model into a quantitative description of industry, residence, workplace, and telecommuting decisions made by U.S. workers in the years leading up to 2020. We focus our analysis on the 48 contiguous United States and the District of Columbia.

We define a model location as the intersection of a Census Public Use Microdata Area (PUMA) and a county.[21] In densely populated areas, where there are many PUMAs to a county, each PUMA is a model location. This allows us to take advantage of geographically-detailed data and depict patterns within metro areas. In rural areas, where there may be several counties in a single PUMA, each location is a county. Defining locations this way and dropping two locations with missing wage data, we end up with 4,502 model locations.

[21] The Census Bureau designs PUMAs to have between 100,000 and 200,000 residents. Thus, large metropolitan areas have many model locations: The New York metro area has 147 distinct model locations.

4.1. Data

Our next step is to populate these locations with relevant data. For each one, we use information on the resident population, the number of jobs, wages, floorspace prices, and non-tradable output prices. We also use information on bilateral commuting flows and times. We focus on the period of 2012–2016.[22] The total number of workers by education level and occupation type, I^{so}, is calculated from ACS data as described in Section 2.

Residents, jobs, and commuting. To obtain information on resident population, jobs, and commuting flows, we turn to the LEHD Origin-Destination Employment Statistics (LODES2016) database. We use averaged data for the years 2012–2016. LODES provides workplace and residence job counts separately by education level or by industry at the Census block level, which we aggregate up to the level of our model locations. We divide NAICS categories into tradable and non-tradable industries and divide education levels into "college" and "non-college" in the same way that we described in Section 2. LODES also provides commuting flows between each pair of locations.

Wages. We use the Census Transportation Planning Products (CTPP2016) database and the American Community Survey (ACS2016) microdata for 2012–2016 to obtain estimates of average wage by industry m and education s for each location j: $\widehat{w}_{mj}^{s}$. In our model, firms pay workers for their labor as well as for floorspace expenses. We convert observed wages $\widehat{w}_{mj}^{s}$ into their model counterpart w_{mj}^{s} by applying commuting flows and effort predicted by the model. To estimate wage differences between on-site workers and telecommuters, we also use the ACS data. The data and our methodology are described in Appendix Sections A.3 and A.2.

Non-tradable goods prices. We use the Bureau of Economic Analysis Regional Price Parities for the "Services other than real estate" category as a proxy for non-tradable output prices. We use data at the metropolitan statistical area (MSA) level, if available, and apply the same price level to all locations within a single MSA. For the remaining locations, we apply the state non-metropolitan price level from the database. For each location we take the average across the years from 2012–2016.

Floorspace prices. To obtain local rental prices of floorspace, we estimate hedonic rent indices for each PUMA using self-reported housing rents from the ACS for the period from 2012 to 2016. Appendix Section A.5 provides more details.

Commute times. Bilateral travel times are obtained from the CTPP survey data for the period 2012–2016, with some imputations to fill in missing trajectories. Details can be found in Appendix Section A.6.

[22] The choice of the time period is motivated by the fact that our wage and commuting time data is aggregated at five-year intervals and this is the most recently available interval prior to the pandemic.

4.2. Parameterization

Model parameters can be divided into three sets: those we set externally, those we estimate (both summarized in Table 3), and those we calibrate internally (summarized in Table 3).

Table 3. Externally determined and estimated parameters

Parameter	Description	Value	Comments
γ	Consumption share of housing	0.24	Davis and Ortalo-Magné (2011)
α	Labor share in production	0.82	Valentinyi and Herrendorf (2008)
ξ	Elasticity of substitution between college and non-college labor	2	Middle of the 1.5-2.5 range in Card (2009)
σ	Fréchet elasticity of industry shock	1.4	Lee (2020)
ϵ	Fréchet elasticity of location shock	4.026	Estimated – see Section 4.2.2
λ	Elasticity of local productivity to employment density	0.086	Heblich, Redding, and Sturm (2020)
χ	Elasticity of local amenity to population density	0.172	Heblich, Redding, and Sturm (2020)
ψ	Contribution of telecommuters to productivity externalities	{0,1}	We run separate counterfactuals with $\psi = 0$ and $\psi = 1$
$\kappa + \tau$	Elasticity of commuting cost to commuting time	0.011	Average of estimates from Ahlfeldt, Redding, Sturm, and Wolf (2015) and Tsivanidis (2019)
η_i	Price elasticity of floorspace supply	Various	Baum-Snow and Han (2021)

Note: The table lists parameters determined externally to the calibration process

4.2.1. Externally Set Parameters

We set the consumption share of housing, $\gamma = 0.24$, following Davis and Ortalo-Magné. (2011). Valentinyi and Herrendorf (2008) estimate that the combined share of land and structures in the U.S. is equal to 0.18. Thus, we set the labor share in the production of tradable and non-tradable goods, α, equal to 0.82. The elasticity of substitution between college and non-college labor, ξ, is set to 2, in the middle of the range between 1.5 and 2.5 reported by Card (2009). We set the Fréchet elasticity of the distribution of industry choice shocks, σ, equal to 1.4, following Lee (2020). We borrow the estimates of the elasticities of local productivity and amenities with respect to density from Heblich, Redding, and Sturm (2020), and set $\lambda = 0.086$ and $\chi = 0.172$. To evaluate the sensitivity of our results to these two values, we run counterfactual experiments where each of these values is set to zero (see Section 5.3) Due to the lack of empirical evidence and appropriate calibration targets, we do not take a stance on the relative contribution of remote workers to the productive externalities, ψ. Instead, we will consider counterfactual scenarios with two extreme values: $\psi = 0$ and $\psi = 1$ (see Section 5.3).

In our model, the expected utility of a worker is decreasing in commute time for two reasons. First, greater commuting time increases the disutility of commuting (with elasticity κ). Second, it increases the distance penalty (with elasticity τ). Note that most existing urban models with commuting did not have remote work and, in terms of our model, had all workers have $\theta = 1$. Therefore, because for a worker with $\theta = 1$ we have $g_{ij} d_{mij}^{so} = e^{(\kappa+\tau)t_{ij}}$, the term $\kappa + \tau$ in our model is analogous to the elasticity of the commuting cost with respect to commuting time in a model without remote work. Using the same functional form of the commuting cost, Ahlfeldt, Redding, Sturm, and Wolf (2015) estimate the elasticity of about 0.01, while Tsivanidis (2018) estimates a value of 0.012. We set $\kappa + \tau = 0.011$, the average of these two estimates. Below we calibrate τ and thus identify κ.

To allow for the possibility that in our counterfactuals floorspace development responds differently to changes in demand across locations, we let the elasticity of floorspace supply, $(1 - \eta_i)/\eta_i$, vary by location. Baum-Snow and Han (2021) estimate elasticities of floorspace supply with respect to prices for Census tracts in over 300 metro areas.[23] We aggregate these to the level of our model locations using population weights. A nationwide map of elasticities at the level of model locations can be found in Figure J.5. The advantage of these estimates is their geographic granularity. At the same time, they are significantly lower than previous studies have found.[24] In Appendix Section I.3 we show that the results of our counterfactuals change little if we use higher values of the elasticity.

4.2.2. Estimation of the Fréchet Elasticity of Location Choice

To obtain the value of the Fréchet elasticity ϵ, we construct the log-likelihood function that combines the number of commuters on each (i, j) link and the probability of commuting along this link:

$$\ln\mathcal{L} \equiv \sum_{i\in\mathcal{J}} \sum_{j\in\mathcal{J}} N_{ij} \ln\left[\frac{\bar{X}_i \bar{E}_j e^{-(\kappa+\tau)\epsilon t_{ij}}}{\sum_{i'\in\mathcal{J}} \sum_{j'\in\mathcal{J}} \bar{X}_{i'} \bar{E}_{j'} e^{-(\kappa+\tau)\epsilon t_{i'j'}}}\right]. \tag{4.1}$$

In this expression, N_{ij} is the number of commuters from i to j in the LODES data, $\bar{X}_i$ and $\bar{E}_j$ are origin and destination fixed effects that subsume all relevant local variables that appear in the conditional location choice probability (equation 3.4), and t_{ij} is the commuting time from i to j.[25] At this stage, we cannot separately identify $\kappa + \tau$ and ϵ, and we estimate the value of $(\kappa +$

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[23] The model locations for which no estimates exist are mostly rural. Since, according to Baum-Snow and Han (2021), there is a strong negative relationship between elasticity and population density, we assume that the elasticity in these places takes the maximum observed value.

[24] At the level of our model locations, elasticities vary from 0 to 0.95, and the population-weighted mean is 0.45. Thus, η_i ranges from 0.51 to 1 and the mean is 0.72. For comparison, Saiz (2010) estimates the elasticities to be on average 1.75 at the metro area level. baum2019microgeography discuss the reasons for this discrepancy. Moreover, in our model the parameter η_i corresponds to the land share in the production. Thus, the mean land share in our model is higher than most existing estimates: e.g., Albouy and Ehrlich (2018) find that the land share is about 1/3 for the U.S.

[25] Because LODES and CTPP do not distinguish commuters and telecommuters, we estimate this relationship assuming that all observations commute to the job site all the time, i.e., are workers with $\theta = 1$. Moreover,

$\tau)\epsilon$ using Poisson pseudo maximum likelihood (PPML).[26] Prior to estimation, we set $N_{ij} = 0$ for all pairs with commuting times of more than 3 hours one way.[27] As reported in Table 4, our estimate of $(\kappa + \tau)\epsilon$ is 0.0443. To recover ϵ, we use the chosen value $\kappa + \tau = 0.011$, as discussed in Section 4.2.1, and obtain $\epsilon = 0.0443/0.011 = 4.026$.

Table 4. Estimation of gravity equation

t_{ij}	-0.04428
	(0.00013)
Observations	20,268,004
Pseudo R^2	0.967

Note: This table reports estimated coefficients for equation (4.1). Standard errors are in parentheses. Estimation includes residence and workplace fixed effects.

4.2.3. Model Calibration and Inversion

The calibrated values of relative productivity ν_m^s, the elasticity of substitution between on-site and remote work ζ_m^s, and aversion to remote work ς_m^s, are shown in Table 5. While we jointly calibrate these and several other parameters, these three sets of parameters are primarily determined by three sets of targets.

The first set is comprised of the relative wages of remote workers. In our model, we calculate, for workers in each industry and education group, the average wage of telecommutable workers who work on-site less than 20% of the time, $\overline{w}_m^{sT}(\theta < 0.2)$; and the average wage of telecommutable workers who work on-site more than 80% of the time, $\overline{w}_m^{sT}(\theta > 0.8)$. We target each ratio $\overline{w}_m^{eT}(\theta < 0.8)/\overline{w}_m^{eT}(\theta > 0.8)$ to the corresponding number from Table 2.

The second set of targets consists of the variance for each group of the choice of on-site work frequency for choices which fall between 1 and 4 days per week, i.e., $0.2 \leq \theta \leq 0.8$. We target this middle range so that the moment is more distinct from the average freqency, which is heavily influenced by the masses of workers with $\theta < 0.2$ and $\theta > 0.8$. These variances are calculated from the SIPP data, as described in Section 2.

because we only observe employment levels but not flows by either industry or education, we cannot estimate the Fréchet elasticity separately for different worker types.

[26] The primary reason why we use the PPML approach rather than more common OLS estimation is that 98.4% of location pairs in our data have zero flows. As Dingel and Tintelnot (2020) show, the sparse nature of commuting matrices may result in biased OLS estimates of the Fréchet elasticity and poor model fit.

[27] Out of 139 mln commuters we observe in LODES, 9.8 mln travel between locations that are over 3 hours apart. While some of these observations could be full-time telecommuters, due to reasons outlined in Graham, Kutzbach, and McKenzie (2014), many of these long commutes arise due to errors in assigning work or residence locations. In addition, the evidence in Figure 2 shows that most telecommuters do not live extremely far from their employers and therefore are unlikely to be dropped from our analysis.

The third set of targets is comprised of mean fractions of time worked on-site for workers in each industry and education group $\bar{\theta}_m^s \equiv \sum_o \sum_i \sum_j \pi_{mij}^{so}\theta_{mij}^{so} / \sum_o \sum_i \sum_j \pi_{mij}^{so}$. We target each ratio to match the type-specific averages calculated from SIPP data.

Next, we calibrate the elasticity of the distance penalty to the commuting time, τ, as follows. If a person is unable to telecommute, it is observationally equivalent for them to live close to their work because of the commute cost d_{ij} or because of distance penalty g_{ij}. Once workers can telecommute, however, the distinction becomes very important. If commuting cost is all that matters, our model predicts that the average telecommuter will live very far from their workplace. If, on the other hand, distance penalty is all that matters, there is no substantive difference between commuters and telecommuters in terms of residential location choices. Either of these extremes would be inconsistent with the *stylized fact #4* presented in Section 2 Thus, we first calculate the average distance in kilometers between residence i and job site j, dist_{ij}, separately for "full-time commuters" (defined as those with $\theta > 0.9$) and telecommuters ($\theta \leq 0.9$). Then, we calibrate τ so that the ratio of average distances, is the same in the model and in the data.

Table 5. Internally calibrated parameters

Parameter	Description	Value	Target
	Productivity of remote work:		*WFH mean wage differentials:*
ν_S^L	Non-college, non-tradable	0.9734	$\frac{\bar{w}_S^{LT}(\theta<0.1)}{\bar{w}_S^{LT}(\theta<0.9)}=0.985$
ν_G^L	Non-college, tradable	1.1351	$\frac{\bar{w}_G^{LT}(\theta<0.1)}{\bar{w}_G^{LT}(\theta<0.9)}=1.026$
ν_S^H	College, non-tradable	1.0114	$\frac{\bar{w}_S^{HT}(\theta<0.1)}{\bar{w}_S^{HT}(\theta<0.9)}=1.024$
ν_G^H	College, tradable	1.2054	$\frac{\bar{w}_G^{HT}(\theta<0.1)}{\bar{w}_G^{HT}(\theta<0.9)}=1.052$
	Elasticity of substitution between on-site and remote work:		*Variance of WFH frequency:*
ζ_S^L	Non-college, non-tradable	4.1884	$Var(\theta_S^L\|\theta\in[0.2,0.8])=0.0356$
ζ_G^L	Non-college, tradable	3.8924	$Var(\theta_G^L\|\theta\in[0.2,0.8])=0.0367$
ζ_S^H	College, non-tradable	4.3548	$Var(\theta_S^H\|\theta\in[0.2,0.8])=0.0351$
ζ_G^H	College, tradable	3.0330	$Var(\theta_G^H\|\theta\in[0.2,0.8])=0.0273$
	Aversion to work from home:		*Average commuting frequency:*
ς_S^L	Non-college, non-tradable	3.0565	$\bar{\theta}_S^L=0.97$
ς_G^L	Non-college, tradable	2.9367	$\bar{\theta}_G^L=0.94$
ς_S^H	College, non-tradable	3.1087	$\bar{\theta}_S^H=0.91$
ς_G^H	College, tradable	2.9130	$\bar{\theta}_G^H=0.82$
β	Consumption share of non-tradables	0.6895	Ratio between average wages in the tradable and non-tradable sectors = 1.23
τ	Elasticity of distance penalty g_{ij}.to commuting time	0.0024	Ratio between telecommuters' and non-telecommuters' distance to work = 0.338

Note: The table lists parameters determined internally during the calibration process

Spending on non-tradable goods is an important determinant of wages in the non-tradable sector. Therefore, we calibrate β, the expenditure share on non-tradable goods, so that the ratio between the mean wages in the tradable and non-tradable sectors, is the same in the model and in the data.

We also need to quantify several vectors of location-specific fundamentals, and we do this by inverting the model. These fundamentals are land-adjusted exogenous productivity $\tilde{a}_{mi} \equiv a_{mi}\Lambda_i^{-\lambda}$, land-adjusted exogenous amenities $\tilde{x}_{mi}^s \equiv x_{mi}^s\Lambda_i^{-\chi}$, land-adjusted productivity of floorspace developers $\tilde{\phi}_i \equiv \phi_i\Lambda_i$, residential amenities X_{mi}^s, workplace amenities E_{mj}^s, and low-skilled productivity shifter ω_{mj}.[28]

[28] Separate identification of land area Λ_i is not required for the model.

These parameters are pinned down by using the following local data. Labor productivity parameters $\tilde{a}_{mi}$ and ω_{mj} are determined from observed wages by industry and skill. Floorspace productivity parameter $\tilde{\phi}_i$ is determined from observed housing prices. Residential amenities $\tilde{x}^s_{mi}$ are determined from total population of a location. In the data we observe total residents and employment by industry or education for each location, but not by both characteristics at the same time. This requires us to assume that residence and workplace amenities can be decomposed into education- and industry-specific components as $X^s_{mi} = X_{mi}X^s_i$ and $E^s_{mj} = E_{mj}E^s_j$. Needless to say, in practice locations differ in many other important ways, e.g., climate, access to transportation, etc. All these differences are implicitly captured by the amenity parameters.

The following result states that, given observed data and economy-wide parameters, there are unique vectors of location-specific fundamentals, consistent with the equilibrium of the model.

Proposition 1. Given the data, $N_{R,mi}$, $N_{W,mj}$, $N^s_{R,i}$, $N^s_{W,j}$, I^{so}, $\widehat{w}^s_{mj}$, q_i, p_i, t_{ij}, estimated local land shares η_i, and economy-wide parameters, α, β, γ, ϵ, ζ, κ, λ, ν^s_m, ς^s_m, ξ, σ, τ, χ, and ψ, there exists a unique set of vectors, $\tilde{a}_{mi}$, $\tilde{x}^s_{mi}$, $\tilde{\phi}_i$, X_{mi}, X^s_i, E_{mj}, E^s_j, and ω_{mj}, that is consistent with the data being an equilibrium of the model.

Proof. See Appendix Section C.2

4.3. Model Fit

Stylized facts about telecommuting. How does our model do in matching the four stylized facts laid out in Section 2? For *stylized fact #1*, while we match the fraction of telecommutable workers by education and the total number of workers in each industry during our calibration, the model endogenously produces the fraction of telecommutable workers by industry. Figure 1 reported that the share of those who cannot work remotely is 81.1% for non-college workers in the non-tradable sector, 71.1% for non-college workers in the tradable sector, 46.7% for college workers in the non-tradable sector, and 31.2% for college workers in the tradable sector. The corresponding numbers in our model are 77%, 75.9%, 40.4%, and 38.8%. Though the ranking is preserved, the industry telecommutability gap is smaller than in the data. This is not surprising as industry is a free choice in our model and we do not have any parameters to represent the structural links between certain occupations and industries that almost certainly drive most of the gap in the data.

For *stylized fact #2*, our model successfully produces the gap in telecommuting *uptake* across both education levels and industries. Figure 1 showed that the fraction of those who work from home at least one paid full day per week is 3.9% among non-college workers in the non-tradable sector, 7.8% for non-college workers in the tradable sector, 12.7% for college workers in the non-tradable sector, and 26.1% for college workers in the tradable sector. The corresponding numbers in our model are 3.6%, 8%, 8.8%, and 28.2%.

The model ably reproduces *stylized fact #3*, as demonstrated in Figure 4. By targeting the mean frequency for each education-industry pair and the variance for the interior of the distribution,

$\theta \in [0.2,0.8]$, we can reproduce the heavy right tail and, to some extent, the bimodality of the distribution. One exception is the distribution for college graduates in tradable industries. Due to the relatively low calibrated elasticity of substitution between on-site and remote work, our model generates a lower number of full-time commuters compared to the data. *Stylized facts #4 and #5* we match by construction, as the relative wages and relative distance to the job site of telecommuters are calibration targets.

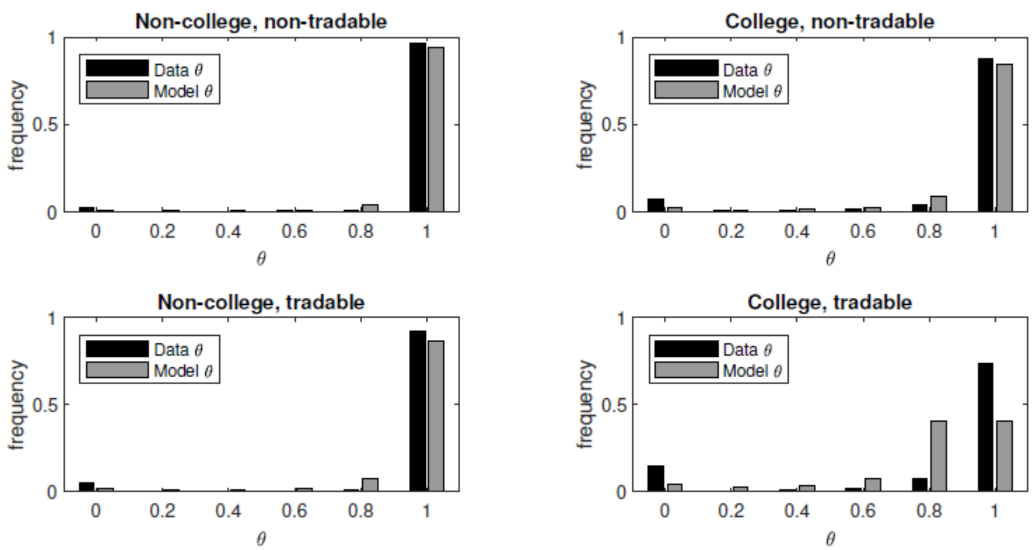

Figure 4. Telecommute frequency, data vs. benchmark model

Note: “Data” reflects averages from SIPP, as described in Section 2. “Model” shows values predicted by the calibrated model. A bar at a given θ includes values $\theta \pm 0.1$. Values of θ greater than 0.9 are included in the bar at $\theta = 1$; values less than 0.1 are included with $\theta = 0$.

Commuting flows. We match residents and jobs by education and industry in each location, but leave the model free to predict commuting flows between locations. Thus $\pi_{ij} \equiv \sum_s \sum_o \sum_m \pi_{mij}^{so}$ is an untargeted moment that we can use to evaluate our model.[29] Figure J.1 shows that the correlation between model and data flows is 0.93.

4.4. Discussion of Calibrated Remote Work Parameters

The values arrived at for relative productivity parameters, elasticities of substitution between remote and on-site work, and parameters for non-pecuniary aversion to remote work, merit some discussion. Our calibration sets the relative productivity of remote work higher in the tradable than in the non-tradable industry, and higher for college compared to non-college workers. This establishes a clear hierarchy, with non-college workers in the non-tradable sector being about 2% less productive working full time from home versus full time in the office, and college workers in the tradable sector being about 20% more productive working all the time at

[29] Flows by industry, occupation, education are unobserved and cannot be compared to model flows.

home.[30] Then, our calibration sets the elasticity of substitution between remote and on-site work higher in the non-tradable industry than the tradable industry, with values ranging from 3 to 4.4.[31]

Taken together, these values imply that, compared to workers in the non-tradable industry, workers in the tradable industry are relatively more productive at home but their time at home and time on-site are less substitutable. The tradable sector includes many knowledge-intensive industries such as finance and information technology. One interpretation of the lower elasticity of substitution could be that in this sector there is greater complementarity between individual tasks that are relatively easy to do at home, and knowledge-sharing and coordination which are more efficiently accomplished on-site.

We also note that the finding of modestly higher overall productivity for remote work in the tradable sector is consistent with some empirical evidence. In a carefully controlled experiment, Bloom, Liang, Roberts, and Ying (2015) find that Chinese call center workers were 13% more productive working from home. This is a result for a narrow category of worker—call center operator. A more recent study conducted during the pandemic by Bloom, Han, and Liang (2022) randomizes work from home on 1600 engineers in a large multinational company. It finds no differences in promotions and performance evaluations, lower quit rates, and less frequent sick leaves, suggesting that work from home is at least as productive as work in the office. Furthermore, surveys conducted by Barrero, Bloom, and Davis (2021) since March 2020 indicate that workers of all types self-evaluate that they are, on average, more productive working from home. Figure 5 compares these self-reported differences in productivity with our calibrated relative productivity of remote work. It shows that, despite some differences in levels, the ranking of values across categories for both our calibration and the survey is identical.

As for the aversion to remote work, our calibration yields values of around 3 for each of the worker categories. This indicates the presence of significant non-pecuniary barriers to remote work for all types of workers.[32]

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[30] In contrast, Davis, Ghent, and Gregory (2022) estimate relative productivities of approximately 0.35 for both high and low-skilled workers. Combined with their estimated worker-type-specific TFPs, this implies that a high or low-skilled remote worker who worked all of the time from home would only earn half of the wage of an equivalent non-remote-capable worker.

[31] Davis, Ghent, and Gregory (2022) estimate a single elasticity of substitution which applies to all worker categories. They find a value of 3.5, squarely in the middle of the values we find.

[32] While not directly comparable to the parameters in our specification, Davis, Ghent, and Gregory (2022) also specify a kind of work from home preference parameter for high and low-skilled workers. Their estimated values indicate a positive preference for having the option of working from home. Presumably this is necessary to counterbalance their low estimated productivity of remote work.

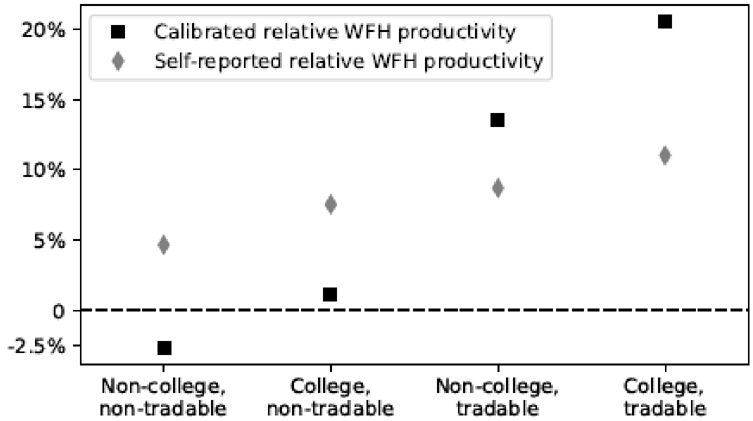

Figure 5. Work from home productivity

Note: Black squares represent the calibrated relative productivity of work from home, ν_M^S. Gray diamonds represent self-reported difference in work-from-home productivity Compared to the on-site productivity from Barrero, Bloom, and Davis (2021).

5. Implications of an increase in Telecommuting

In this section, we study the long-run impact of the rise in work from home as a result of a permanent preference shock which reduces worker distaste for working from home, ς_m^s. We explore the shifts in residence, jobs, prices, and commuting patterns predicted by our model, as well as welfare implications of these changes. To validate our approach, we show that our model has considerable success in predicting local changes in population and real estate prices that have already occurred since the beginning of Covid-19 pandemic. Finally, we provide some evidence that the preference component of the Covid-19 telework shock is likely more significant than the technology shock component.

5.1. Counterfactual Setup

Our baseline assumption is that the increase in remote work is driven by falls in the aversion to telecommuting experienced by workers of each skill/industry combination: ς_m^s for $s \in \{H, L\}$ and $m \in \{G, S\}$.[33] How do we determine the size of the changes in these four parameters? Barrero, Bloom, and Davis (2021) conducted repeated surveys of workers where they self-report their employers' plans for whether a worker is expected to work remotely zero, one, two, three, four or five days a week post-Covid. The survey is representative of the U.S. labor force. From these data we calculate a post-pandemic mean on-site working frequency for each worker type, and lower the aversion to remote work to match it. We assume that remote workers do not contribute to productive externalities: i.e., we set $\psi = 0$. We examine the implications of this assumption in Section 3.3.

[33] As discussed in Section 3.6, the equilibrium of the model need not be unique. We follow Tsivanidis (2019) in in focusing on the counterfactual equilibrium that is computed using the benchmark equilibrium as the starting point and turns out to be unique. Such counterfactual equilibria may be more likely to occur, for instance, due to path dependence (Allen and Donaldson, 2020).

Figure 6 compares the distributions of commuting frequency indicated by the Barrero, Bloom, and Davis (2021) survey with those predicted in the counterfactual. In spite of the fact that only one moment—the mean—from each distribution is targeted, the two sets of distributions line up very well.

Table 6 shows the change in the aversion to telecommuting for each worker type that was necessary to achieve the targeted increases in telecommuting. Non-college workers in both sectors see large drops in their aversion to telecommuting, while college-educated workers see smaller drops, ending up with higher levels of aversion than their non-college counterparts. One possible interpretation of this result is that even once the technological and cultural barriers to remote work are removed, college workers have some reasons to come to the office—possibly information sharing and networking—that may be less important for non-college workers. In Appendix Section I.2, we study a counterfactual in which all types of workers experience the same change in work-from-home aversion. This does not change the results in any major way.

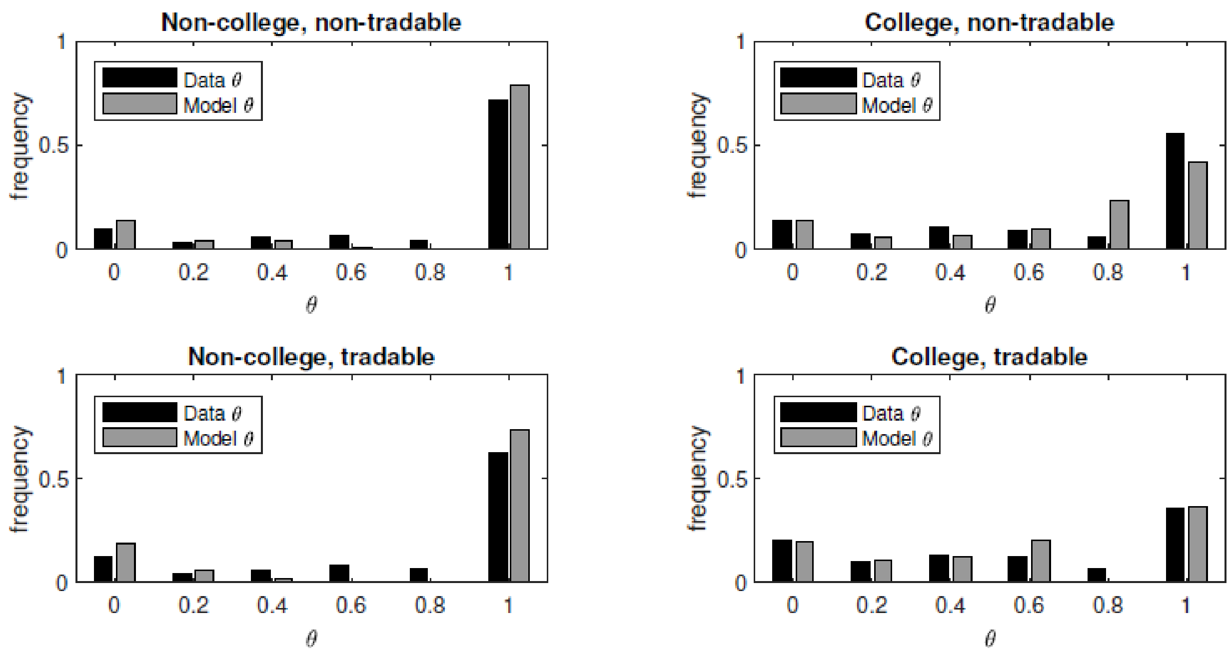

Figure 6. Telecommute frequency, survey prediction vs. counterfactual model

Note: Black squares represent the calibrated relative productivity of work from home, ν_M^S. Gray diamonds represent self-reported difference in work-from-home productivity Compared to the on-site productivity from Barrero, Bloom, and Davis (2021).

Table 6. Relative aversion for remote work, baseline vs. counterfactual

Description	Variable	Benchmark	Counterfactual
Non-college, non-tradable	ς_S^L	3.0565	1.1273
Non-college, tradable	ς_G^L	2.9367	1.0738
College, non-tradable	ς_S^H	3.1087	1.8517
College, tradable	ς_G^H	2.9130	1.6963

Note: The table shows calibrated values of the relative aversion for remote work

5.2. Results

Permanently decreasing the aversion for remote work triggers important shifts in the spatial distribution of residents, jobs and real estate prices. These add up to a significant effect on aggregate productivity and welfare. We will describe the spatial shifts first, and then proceed to analyze the aggregate effects.

5.2.1. Spatial Shifts

Distribution of residents. As panels (a) and (b) in Figure 7 show, increased productivity of remote work leads to a reallocation of residents away from the densest locations and biggest cities, towards sparser locations and smaller cities. While there is much heterogeneity in the changes which is not explained by the crude ranking of locations and cities, the *average* trend is monotonic. We calculate that about 1/3 of relocations happen within metro areas and 2/3 across metro areas. This finding, together with the evidence that our model's predictions match observed changes in residents during 2019–2021 both within and across metro areas (see Section 5.4), points to the importance of modeling both the system of cities and their internal structure when studying the implications of telecommuting. Appendix Section D describes how we measure the relocation of residents.

In the five largest metro areas, New York's population grows 0.5%, Chicago's shrinks by slightly less than half a percent, and Los Angeles, Dallas and Houston each lose a bit more than 3%. Table J.1 provides details for changes in residents in 50 largest metro areas, while Figure J.2 displays predicted changes on a map.

Our base of residents is made up of two distinct groups who react very differently to the change. Panel (c) shows that non-telecommutable residents shift from less to more dense locations, while panel (d) shows that telecommutable residents move away from denser places towards the periphery. This is because workers who cannot work remotely take advantage of falling prices in city centers and larger cities to relocate closer to better-paying jobs. Meanwhile, remote-capable workers, now facing fewer obstacles to working at home, follow lower prices out of city centers and from larger to smaller cities. The latter trend is stronger and dominates the overall shift in residents—in spite of the fact that telecommutable workers are outnumbered nearly 2 to 1.

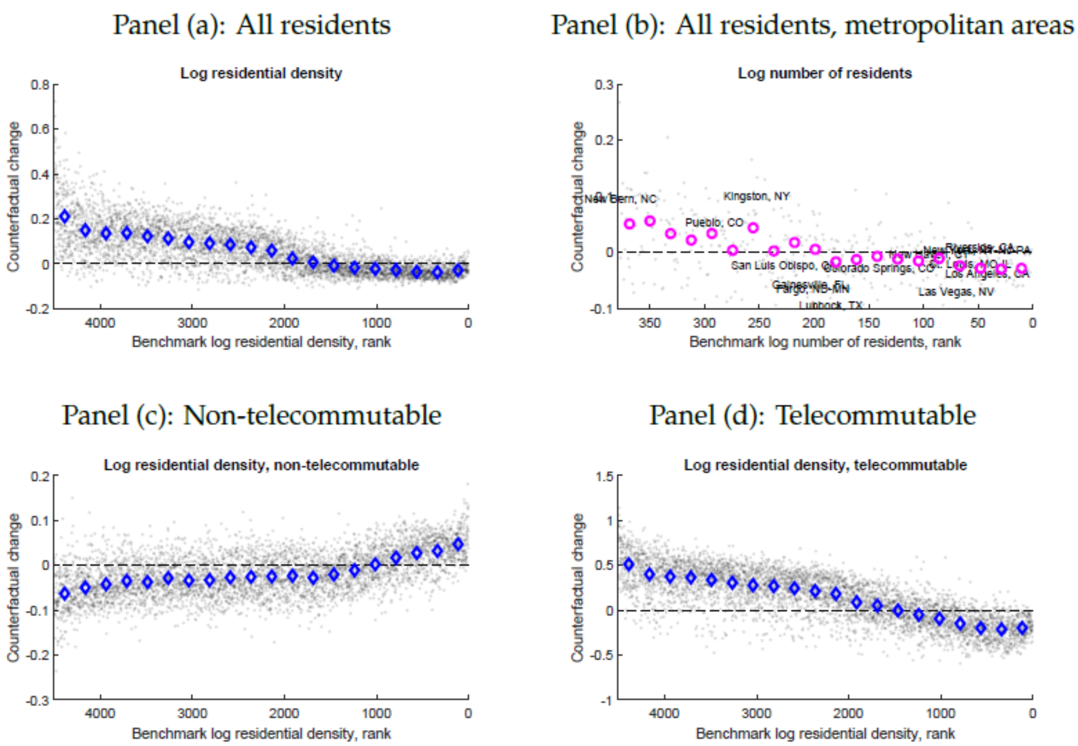

Figure 7. Change in Residents

Note: Panel (a) shows the relationship between residential density rank for model locations and counterfactual change in log residential density. Panel (b) shows the relationship between total resident rank for metro areas and the counterfactual change in log total residents. Panel (c) repeats the exercise for non-telecommutable residents by model location, while panel (d) does the same for telecommutable residents. Scatterplots in gray show individual model locations of MSAs while diamonds or circles represent averages by ventile: i.e., below the 5th percentile, from the 5th to the 10th, etc.

Distribution of jobs. In contrast to the overall pattern for residents, the shift in the overall distribution of jobs displays some non-monotonicity. As panel (a) in Figure 8 demonstrates, the density of jobs increases on average in locations which are below the median density, while decreasing in locations which are above the median, and showing little change in the most-dense locations. A similar pattern is observed at the metro area level, as shown in panel (b). Table J.2 provides details for changes in jobs in 50 largest metro areas, while Figure J.3 displays predicted changes on a map.

Decomposing the changes in job location into the two sectors, we see a differential pattern underlying the aggregate shifts. Panel (c) shows that shifts in non-tradable jobs are monotonic, from less- to more-dense locations. Since demand for non-tradable output comes entirely from the local population, these jobs simply follow the residents. The non-monotonicity in the pattern of job shifts comes from the tradable sector. As can be seen in panel (d), locations below the median gain tradable jobs, and so do the very densest locations. This is because the increased productivity of remote work effectively reduces spatial frictions in the labor market, and two types of locations win out in this expanded competition. One is low-density places with low real estate costs. The other is the highest-density places, with high productivity, and also the biggest reduction in real estate costs, as we will see in our discussion of price changes below.[34]

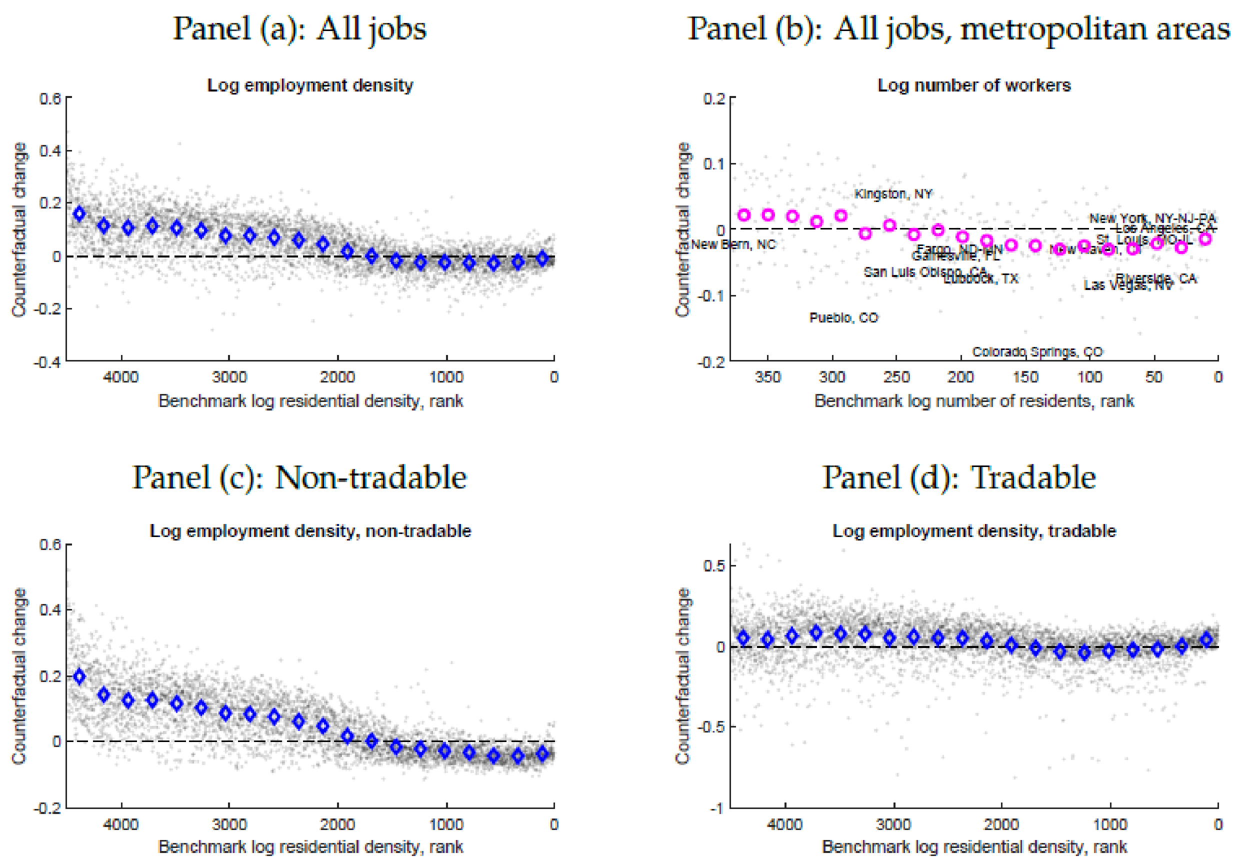

Figure 8. Change in Employment

Note: Panel (a) shows the relationship between residential density rank for model locations and counterfactual change in log job density. Panel (b) shows the relationship between total resident rank for metro areas and the counterfactual change in log total jobs. Panel (c) repeats the exercise for non-tradable jobs by model location, while panel (d) does the same for tradable jobs. Scatterplots in gray show individual model locations of MSAs while diamonds or circles represent averages by ventile: i.e., below the 5th percentile, from the 5th to the 10th, etc.

[34] The correlation between log productivity in the tradable sector and log residents per square km is 0.66.

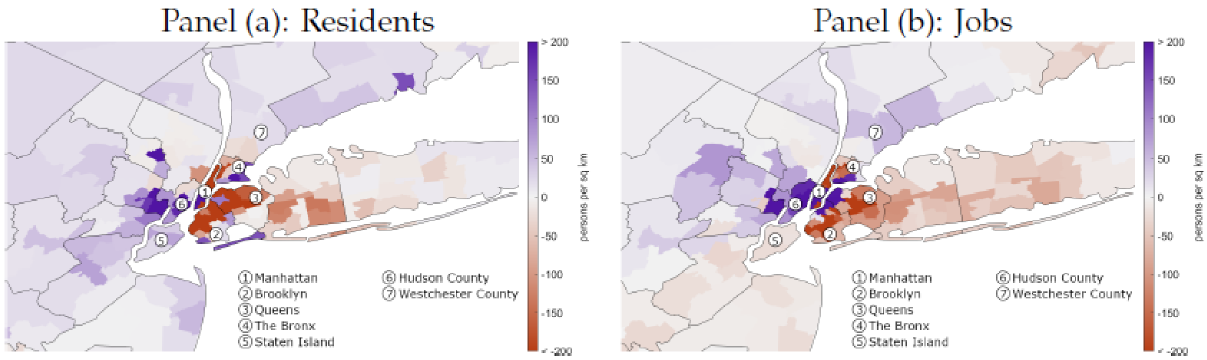

Figure 9. New York metro area, predicted movements of residents and jobs
Note: The maps show absolute changes in the number of residents (panel a) or jobs (panel b) per square kilometer in the main counterfactual exercise.

Zooming in: New York metropolitan area. A closer look at the New York metro area gives us a more concrete idea of how predicted changes in jobs and residents play out at the intra-city level. In panel (a) of Figure 9 we see that there is a large predicted movement of residents out of most of Manhattan, Brooklyn, and Queens. The Bronx, Staten Island, and isolated locations in Manhattan and Queens see significant inflows. Counties in New Jersey and Connecticut and outlying counties in New York state gain residents. This donut-shaped pattern is consistent with the nationwide patterns we reviewed earlier as well as with migration evidence during the Covid-19 pandemic (Ramani and Bloom, 2021).

Panel (b) shows changes in jobs. Downtown and midtown Manhattan, the the parts of Brooklyn, Queens, the Bronx, and New Jersey which are closest to Manhattan, all see strong job gains. Employment growth in highly productive areas like these is largely driven by the growth in telecommutable jobs in the tradable sector. The immediate suburbs to the north of the city see moderate gains, while Long Island and suburbs to the south of the city see job losses.

On the aggregate, the residential population of the New York metropolitan area increases by 0.5% while employment goes up by 1.7% (see Table J.1 and Table J.2). Job gains exceed population gains because, with more common remote work, more workers can access the attractive New York's labor market without having to live there. These workers tend to live in nearby metro areas where housing is more affordable. For example, Philadelphia's residential population barely changes, declining only 0.1%, even though the number of jobs in the metro area falls by 0.8%.[35] Further discussion of results for the New York metro area can be found in Appendix Section F.

[35] Similarly, the Los Angeles metro area experiences a 0.3% job growth while losing 3.5% of its residents. Many of these migrants keep their jobs in Los Angeles but commute less often which allows them to settle in the adjacent Riverside-San Bernardino area where housing costs are lower.

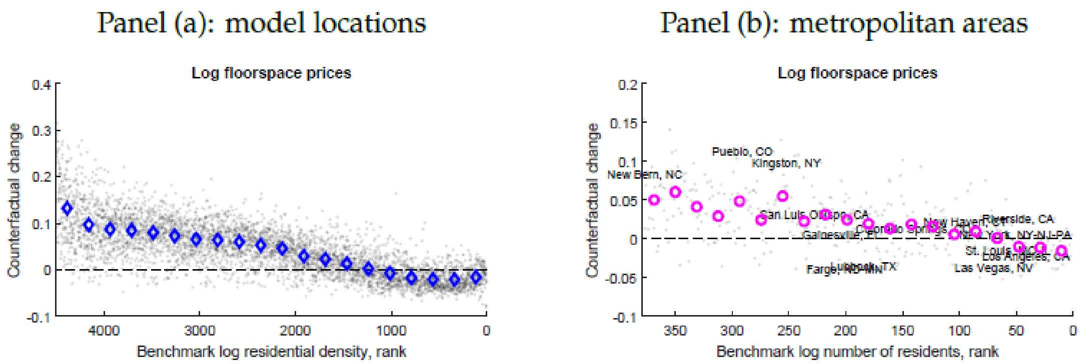

Figure 10. Floorspace prices

Note: Panel (a) shows the relationship between residential density rank for model locations and counterfactual change in floorspace prices. Panel (b) shows the relationship between total resident rank for metro areas and the counterfactual change in floorspace prices. Scatterplots in gray show individual model locations of MSAs, while diamonds or circles represent averages by ventile: i.e., below the 5th percentile, from the 5th to the 10th, etc.

Real estate prices. As a result of reallocation of many residents and some jobs to less dense locations, changes in floorspace prices show a clear negative slope in initial density, as can be seen in Figure 10. Prices increase on average in locations below the top quartile, and decrease in most top-quartile locations. Figure J.4 displays predicted rent changes on a map. Both the location-level and metro-level patterns are consistent with the previously-seen shift of residents and non-tradable jobs to less-dense locations on average driving up demand for floorspace.

5.2.2. Aggregate Results and Welfare Effects

Table 7 summarizes aggregate results for the main counterfactual scenario, broken down by worker type. In what follows, we will discuss each row in turn.

Income and inequality. Workers' income rises by 1.6%, averaging larger gains by those who can work from home against smaller gains or even losses by those who cannot. A major reason for this disparity is that for most workers telework is more productive; therefore, more frequent remote work boosts their incomes. We study the implications of this feature in Appendix Section I.4 where we eliminate productivity differences between on-site and remote work for all types. Among non-telecommutable workers, those without a college degree experience a 0.6% income growth, while college graduates see a 1.7% decline in income. This happens because there are more remote-capable workers among the college-educated and, by supplying a greater amount of labor effort due to working from home more often, they complement the labor effort of non-college workers but compete with college workers who cannot telecommute.

Averaged together, the incomes of the college-educated increase by more than the incomes of their non-college counterparts, which means the overall college wage gap increases (Katz and Murphy, 1992). Interestingly, the college gap for remote-capable workers moves in the opposite direction than the college gap for those who cannot work from home, the former widening and the latter narrowing. In section 5.3 we compare counterfactuals with alternative assumptions, and delve deeper into what drives these disparities.

A basic measure of inequality across individuals, the variance of log incomes across workers, sees no significant change. But inequality across locations, measured as the variance of log average resident income across locations, falls from 0.034 to 0.029. Recent research on the "Great Divergence" across locations in the U.S. suggests that just a handful of "superstar" cities offer great job opportunities and incomes in these areas diverge from the rest of the country (Moretti, 2012; Gyourko, Mayer, and Sinai, 2013). Our findings indicate that, as remote work becomes more common, job opportunities become more widely available to those who do not live in one of the "superstar" cities and, as a result, differences in incomes of residents across locations fall.

Commuting. Due to the reduction in the aversion for remote work, the average worker lives 52% farther, in terms of commuting time, from their workplace, but spends 20.5% less time commuting, because their frequency of work from home has increased by 0.9 days per 5-day work week. Workers who cannot work from home, especially college-educated, move closer to their workplaces and enjoy somewhat shorter commutes. Those who can work remotely, on the other hand, increase their distance to work by around 153% for college or 78% for non-college, and cut their total commuting time by 48 to 87 percent.

Commutes across metro areas become more common. In the benchmark economy, 17.7% of workers live and work in different metro areas. In the counterfactual economy, this number goes up to 23.9% as remote work increases the average distance between residence and workplace.[36] While our assumption of the CES production function requires positive inputs of both on-site and remote work for telecommutable occupations, some workers choose very low frequencies of on-site work. In our counterfactual economy, 36% of remote-capable workers choose to work on site one day a month or less, while 20% work on site one day a year or less. For the latter category, commuting time matters very little and the average distance between residence and workplace is between 315 and 400 km depending on worker type.

Prices. Average floorspace prices drop by 0.8%. This can be attributed to two complementary forces. First, the increased desire for remote work increases demand for office space in residence locations where prices, on average, are lower than in the dense downtown areas where most jobs are. Second, demand for residential floorspace moves to more supply-elastic locations which tend to be farther from central areas, and which now face lower effective commuting costs. This relocation of demand is counteracted by the overall rise in worker income, which puts upward pressure on prices. The average price paid for residential floorspace paid by telecommutable workers falls by 1.3% for college-educated and 0.5% for non-college-educated. Non-telecommutable workers move to denser locations. Even though prices are falling on average in these denser locations, they are still more expensive than the peripheral

[36] In these calculations we exclude workers who either live or work outside of a metropolitan area. Note that we do not match flows in the quantitative model. But the share of cross-MSA jobs in the data is very similar: 16.7%.

locations they are moving from, leading to slightly higher average floorspace prices for this group.

Table 7. Aggregate results

		Non-college			College		
	All workers	All	Non-tel.	Tel.	All	Non-tel.	Tel.
Income, % chg	1.6	0.9	0.6	1.8	2.8	-1.7	5.3
Average time to work, % chg	52.0	50.7	-0.4	152.6	54.8	-0.7	77.5
Time spent commuting, % chg	-20.5	-18.0	-0.4	-86.6	-27.0	-0.7	-47.6
Average WFH days/week, chg	0.9	0.8	—	3.5	1.2	—	2.9
Floorspace prices, % chg	-0.8	-0.5	0.6	-4.3	-1.3	0.2	-2.4
Non-tradables prices, % chg	3.5	3.6	3.6	3.4	3.4	3.5	3.4
Welfare, % chg							
Consumption only	-0.8	-1.5	-2.2	0.2	0.6	-4.2	3.2
+ commuting	0.8	0.0	-2.0	6.0	2.2	-3.9	5.7
+ amenities	0.8	0.0	-0.7	2.1	1.9	-1.7	4.0
Total welfare	7.2	4.0	-1.5	46.9	20.5	-3.4	28.0

Note: The table shows results of the main counterfactual exercise, as described in the text. "tel." refers to telecommutable workers, and "non-tel." to non-telecommutable workers. Price changes refer to the change in the average price faced by a member of the indicated group of workers.

Non-tradable prices increase by around 3.5% for everybody. This can be attributed to a combination of the increase in income, and a movement of demand to less-dense places which tend to also have lower workplace amenities for the non-tradable sector.[37]

Workers' welfare and landowners' income. Consumption of goods and housing go up for telecommuters and down for non-telecommuters, so that consumption for the average worker declines slightly, by 0.8%. This is the net result of the 1.8% increase in income and the 0.8% fall in floorspace prices, outweighed by the 3.5% increase in the price of non-tradables. Utility loss from lower consumption is more than offset by gains from less time spent commuting—when adding commute times to changes in utility, the average worker comes out 0.8% ahead. Gains from reduced commute times are unevenly distributed, being very large for non-college workers in telecommutable occupations, while non-telecommutable workers gain just 0.2 or 0.3 percentage points.[38] Amenities for the average worker do not change. At the same time, telecommutable workers actually reduce the quality of their amenities, due to the fact that

[37] These are locations where, all else equal, it is harder to attract workers due to lower calibrated employment amenities. Hence, non-tradable firms must pay higher wages and pass on that cost to the consumer.
[38] Since our model does not allow for endogenous reduction in traffic due to less frequent commuting, these welfare gains may be understated.

they move to less dense (and, in our model, lower amenity) locations—effectively trading low housing costs, and possibly a better idiosyncratic match, for lower amenities.

Overall welfare—expected utility prior to the realization of preference shocks—increases by an average of 7.2%. This is the net result of large gains for telecommutable workers and small changes for the rest.[39] One important reason why welfare gains for those who can telecommute are so large is that, thanks to less frequent commutes, they are able to choose location pairs with higher values of Fréchet shocks, thus satisfying their idiosyncratic preferences for locations. Overall, college workers gain more than non-college ones. This is because even though telecommutable non-college workers gain the most, their numbers are relatively small; while telecommutable workers make up a relatively large proportion of the college-educated group. More details on how we compute welfare changes can be found in Appendix Section E.

One more adjustment to consider is the impact of increased telecommuting on the income earned by landlords. Overall demand for floorspace goes up by 1.9% and, even though it reallocates to places with higher supply elasticity (and, therefore, lower land share), land prices still go up by 1%. While we do not take a stance on the weight of landlords in the social welfare function, it is obvious that this increase in landowners' income would contribute to aggregate welfare gains from increased remote work.

5.3. Alternative Scenarios

We have presented results from the counterfactual in which all endogenous variables adjust and remote work does not generate productive externalities ($\psi = 0$). To understand the relative roles of each of the channels, we run a series of alternative counterfactuals in which we first shut down all of the margins of adjustment, and then re-activate them one by one.

We start with a world in which the aversion to telecommuting decreases but workers are unable to move and floorspace supply does not change. Then we switch on the relocation of workers to new residences and jobs. After that, floorspace supply adjusts. Next, we allow residential amenities and then local productivity to adjust. This last stage brings us to our original counterfactual—the long run with full adjustment. Finally, we let working at home to contribute to productive externalities as much as working on site ($\psi = 1$). Appendix Section G discusses each scenario in detail.

As shown in Table G.1, welfare gains emerge as soon as the work from home aversion falls and telecommutable workers choose to work remotely more often. Allowing for resident and job reallocation does not lead to further average welfare gains but allows those who can work remotely to move to less dense locations and enjoy greater housing consumption, at the same time as those who cannot work from home move a little closer to their jobs. Allowing

[39] Because we do not take a position on whether the calibrated "aversion to telecommuting" parameters, ς_m^s, reflect genuine worker preferences or other kinds of non-pecuniary barriers to remote work, we exclude the shift in these parameters from all welfare change calculations.

developers to respond to changes in residential and commercial floorspace demand leads to further welfare gains. When residential amenities are allowed to adjust, the gains become even stronger. However, when local productivity adjusts (as in our main counterfactual), welfare gains abate because greater amount of telecommuting leads to aggregate productivity losses. Finally, when we let remote workers to contribute to productivity externalities as if they were on the job site, welfare gains are the largest.

5.4. Evidence During Covid-19

The long-run effects of the Covid-19 shock are yet to be seen, but many changes have already taken place since early 2020. How do the predictions of our model regarding changes in residents and real estate prices compare to the shifts we have already observed?[40]

Residents. To test our model's predictions regarding movement of residents, we use Safegraph data on locations of cell phone devices. For each device, Safegraph assigns a "home location" based on where this device is observed spending the night over a period of six weeks.[41] In Appendix Section A.7, we provide more details on the data and show that it is a good proxy for residential population at the model location level. Column (1) of Table 8 shows that our predicted changes have a positive and significant relationship with observed changes in the data. Moreover, this correlation does not merely pick up the negative relationship between initial residential density and the change in population.[42] As Column (2) shows, even after controlling for residential density in 2012–2016 our model predictions retain positive and significant correlation with the data. This suggests that structural reasons beyond density, such as changes in the commuter market access, can explain migration patterns during the pandemic.

Is our model picking up reallocations within or across local labor markets? To answer this question, we first regress observed changes in population on model predictions controlling for commuting zone (CZ) fixed effects. Results in columns (3) and (4) demonstrate that our model predicts a substantial amount of variation in population changes *within CZs*, even controlling for residential density. Then, we aggregate our model predictions to the level of CZs. Columns (5) and (6) show that our model is also successful in predicting changes in population *across CZs*, even when density is taken into account.

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[40] Changes in residents and real estate prices during the pandemic do not only reflect the shift to work from home. They also depend on many other factors absent from our model, e.g., the dislike of density motivated by health considerations, expansionary monetary and fiscal policy, etc.
[41] Couture, Dingel, Green, Handbury, and Williams (2021) also used cell phone data to track population changes during the Covid-19 pandemic.
[42] Althoff, Eckert, Ganapati, and Walsh (2021) and Haslag and Weagley (2021) previously documented a reallocation of residents from the densest to the least dense locations during the pandemic and, as Figure A. 1 shows, our model also predicts a movement to locations with low density.

Table 8. Change in population during Covid-19, model vs. data

	(1)	(2)	(3)	(4)	(5)	(6)
Log chg residents, model	1.378	0.153	1.103	0.298	0.801	0.145
	(0.0318)	(0.0369)	(0.0424)	(0.0526)	(0.0590)	(0.0677)
Log density, data		-0.0711		-0.0537		-0.0477
		(0.00152)		(0.00231)		(0.00319)
Level of obs.	ML	ML	ML	ML	CZ	CZ
CZ fixed effects	No	No	Yes	Yes	—	—
Observations	4502	4502	4453	4453	723	723
R-squared	0.294	0.526	0.692	0.731	0.204	0.392

Note: The table shows estimates from the regressions of log change in residents between December 2019 and December 2021 from Safegraph data on the log change in residents in the model and log residential density in 2012-2016. Standard errors are in parentheses. The regressions are estimates at the level of model locations ("ML"), with or without CZ fixed effects, or at the level of CZS ("CZ"). Regressions at the model location level with CZ fixed effects have fewer observations because some CZs correspond to model locations.

Real estate prices. To evaluate our predictions of changes in real estate prices, we use Zillow data on both residential rents and prices in turn, calculating changes between December 2019 and December 2021. Table 9 shows the results. Comparing columns (1) and (5) with column (3), we can see that while our model does a poor job of predicting changes across CZs, it does a good job of predicting changes that happen within CZs. Similarly, comparing columns (2) and (6) with column (4), we can see that this same assessment also holds true when controlling for initial residential density, meaning that whatever predictive power the model has within CZs cannot be reduced to a simple function of "central" versus "peripheral" locations.[43]

[43] The relationship between initial density and the change in rents during the pandemic has been previously documented. Gupta, Peeters, Mittal, and Van Nieuwerburgh (2021) and Liu and Su (2021) find a significant "flattening" of the relationship between prices/rents and distance to the center in major metro areas for residential real estate, while Rosenthal, Strange, and Urrego (2021) report similar relationship for commercial real estate. Althoff, Eckert, Ganapati, and Walsh (2021) also show that rents fell in the densest and went up in the least dense areas.

Table 9. Change in housing rents and prices during Covid-19, model vs. data

Panel (a): rents						
	(1)	(2)	(3)	(4)	(5)	(6)
Log chg rents, model	0.288	-0.213	0.840	1.500	-0.747	0.582
	(0.252)	(0.284)	(0.341)	(0.458)	(2.248)	(2.960)
Log density, data		-0.0197		0.0166		0.0614
		(0.00527)		(0.00773)		(0.0887)
Level of obs.	ML	ML	ML	ML	CZ	CZ
CZ fixed effects	No	No	Yes	Yes	—	—
Observations	1136	1136	1122	1122	98	98
R-squared	0.00115	0.0133	0.154	0.157	0.00115	0.00617

Panel (b): prices						
	(1)	(2)	(3)	(4)	(5)	(6)
Log chg prices, model	0.131	-0.0295	0.425	0.541	-0.235	-0.0446
	(0.0820)	(0.124)	(0.140)	(0.212)	(0.300)	(0.407)
Log density, data		-0.00504		0.00362		0.00745
		(0.00294)		(0.00493)		(0.0107)
Level of obs.	ML	ML	ML	ML	CZ	CZ
CZ fixed effects	No	No	Yes	Yes	—	—
Observations	4182	4182	4121	4121	688	688
R-squared	0.000611	0.00132	0.341	0.341	0.000895	0.00160

Note: The table shows estimates from the regressions of log change in rents (panel a) and prices (panel b) between December 2019 and December 2021 from Zillow on the log change in floorspace prices in the model and log residential density in 2012-2016. Standard errors are in parentheses. The regressions are estimated at the level of model locations ("ML"), with or without CZ fixed effects, or at the level of CZs ("CZ"). Regressions at the model location level with CZ fixed effects have fewer observations because some CZs correspond to model locations.

5.4. Covid-19: A shock to Technology, or Something Else?

Various authors, including Barrero, Bloom, and Davis (2021), have emphasized the importance of shifting norms and preferences in explaining planned changes in work-from-home behavior following March 2020. Other non-technological explanations, such as a change in corporate policies or a change in the employment bargaining environment, could also possibly be at play. At the same time, we believe that there is strong circumstantial evidence for a technology-shock component to the pandemic. Large investments in remote-complementary capital have been made, and a great deal of learning-by-doing has occurred. Davis, Ghent, and Gregory (2022) conduct a simulation of the effects of an increase in working from home which is driven entirely by improved remote-work productivity.

We test a productivity-driven change within our own framework and find it to be implausible. We do this by running an alternative counterfactual in which planned increases in working from home are driven by an increase in productivity, instead of a reduction in telecommuting aversion. The results are reported in detail in Appendix section H. The productivity shifts required are quite large, ranging between 70% and 200% for the various worker categories. These lead to correspondingly large increases in wages for remote-capable workers.

In the first place, such a dramatic shift in the average wages of such broad categories of workers seems like an unlikely event. It also worsens our model's ability to predict short-run movements of residents across locations and metro areas. Compare the results reported in Table H.3 with those in Table 8: the productivity-driven changes are more weakly correlated with the actual changes, and when initial density is controlled for, they actually become a significant *negative* predictor. One of the reasons becomes clear when comparing Figures H.1 and 7: non-telecommutable workers move more strongly away from the periphery to central locations, dampening the net pattern of core-periphery reallocation. This is also a consequence of gigantic remote worker wage increases—they use their higher incomes to rent more floorspace, pricing non-remote workers out of the rural and suburban real estate markets.

Is it possible that these results depend on the particular data targets we use for relative wages? We run an alternative calibration in which average wages for remote workers in each education-industry category are 8% lower than their non-remote counterparts, and the telecommuting aversion parameters are also lowered so that baseline rates of working from home are still matched. This lines up with Mas and Pallais's (2017) estimate that workers would be willing to give up 8% of wages in exchange for the opportunity to work from home. From this alternative baseline, the required increases in productivity are just as large as before, while the resulting rise in wages of telecommutable workers are 54% for college and 194% for non-college workers.

In yet another alternative calibration, we assume that aversion to telecommuting is zero for all groups, and match baseline rates of telecommuting entirely by adjusting the relative productivity of remote work. This yields parameters which imply that full-time remote workers should earn on average only 1/3rd the wage of a similar, full-time office-based worker—in other words, that full-time remote workers should earns wages as if they were living in a third-world country. From this baseline, large increases in remote productivity do not lead to large increases in remote wages. But this specification is completely contradicted by the data—there are full-time remote workers pre-2020, and after controlling for all observables, they earn about the same as their office-bound counterparts, as shown in Table 2 This last specification, severely low-balling remote work's initial productivity, corresponds with the approach taken by Davis, Ghent, and Gregory (2022). The inconsistency with the initial distribution of wages is not immediately apparent in their framework because it is not capable of generating the full range of observed work-from-home frequencies, so there are actually no full-time remote workers in their model.

We are thus not able to find a configuration in which increased remote work is driven solely by productivity changes which also gives plausible results.[44] At the same time, a shift produced

[44] This result does not depend, for example, on whether or not the change in relative productivity is modeled as being amplified by externalities, as in Davis, Ghent, and Gregory (2022). As discussed in the previous paragraph, the only way to have a productivity change account for 100% of the change in remote work behavior without

entirely by declines in the aversion to telecommuting, representing some combination of worker tastes and social and legal norms, produces reasonable predictions.[45] Therefore, while we believe that both remote productivity and these other forces have changed due to the Covid-19 shock, it appears that the latter changes are more important in driving behavior.

6. Conclusions

In this paper we have sought to better understand a phenomenon which could reshape our work lives and our cities: telecommuting. We build a quantitative spatial equilibrium model of commuting and remote work crafted to conform with key empirical facts of pre-2020 telework, and with the spatial flexibility to investigate the potential for long-run changes in the distribution of jobs and residents. We calibrate the relative productivity and the elasticity of substitution of remote work for on-site work separately for workers of two education levels and two production sectors.

We propose that enforced 2020 workplace distancing was primarily a durable shock to attitudes and policies surrounding remote work, which can be represented in a reduced form way as a shock to workers' preferences. We calibrate a counterfactual where surveys of workers' long-run remote work plans come true. Counterfactual predictions for local changes in residents and real estate prices line up well with actual changes observed 2019–2021. Our model foresees decentralization of workers who can work from home, partially counterbalanced by a weaker centralization of those who cannot; a decentralization of non-tradable employment, partially offset by an increase in tradable employment in the densest, most productive places; and a slight reduction in average real estate prices. Those who can work from home benefit greatly, while those who cannot experience welfare losses, especially when remote workers do not contribute to workplace agglomeration externalities.

Furthermore, we provide evidence that a shock to remote work productivity is not plausible as a sole explanation of a durable move towards remote work, and that changes in tastes, norms and institutional polices are likely more important. Loading the entire change onto remote work productivity leads to implausibly large increases in remote worker wages, which drive predicted population movements that are inconsistent with observed movements as of December 2021. We believe that this has implications for how the long-term component of the 2020 remote work shock ought to be represented in quantitative models.

To sum up, the impact of remote work may be large, but is unlikely to be catastrophic. There will be no "end to big cities." The average big metro area loses about 2.5% of its population, but the very biggest, New York, actually grows by 0.5%. Many of the largest, most productive cities will be able to take advantage of geographically expanded competition to lure additional talent

implausible wage predictions is for the initial productivity of remote work to be extremely low, in a way that cannot be made consistent with data on the distribution of wages across remote work frequencies.

[45] We do not intend to strongly endorse any particular interpretation of the forces represented by "aversion." "Aversion," could also, for example, be interpreted as institutional ignorance about the relatively high productivity of remote work, which was remedied by the experience of Covid-19.

from other cities, and call in remote workers from more distant suburbs. This same phenomenon should also reduce income inequality across residential locations.

Finally, we believe the substantial impacts of increased telecommuting, both observed and potential, suggest this will be an important consideration for quantitative spatial models in the future.

References

ACS (2016): American Community Survey, U.S. Census Bureau. https://usa.ipums.org/usa/. Accessed through IPUMS USA, September 2020.

Ahlfeldt, G. M., S. J. Redding, D. M. Sturm, and N. Wolf (2015): "The Economics of Density: Evidence From the Berlin Wall," *Econometrica*, 83(6), 2127–2189.

Albouy, D., and G. Ehrlich (2018): "Housing productivity and the social cost of land-use restrictions," *Journal of Urban Economics*, 107, 101 – 120.

Allen, T., C. Arkolakis, and X. Li (2020): "On the Equilibrium Properties of Network Models with Heterogeneous Agents," Working Paper 27837, National Bureau of Economic Research.

Allen, T., and D. Donaldson (2020): "Persistence and Path Dependence in the Spatial Economy," Working Paper 28059, National Bureau of Economic Research.

Althoff, L., F. Eckert, S. Ganapati, and C. Walsh (2021): "The Geography of Remote Work," Working paper.

Barrero, J. M., N. Bloom, and S. J. Davis (2021): "Why Working from Home Will Stick," Working Paper 28731, National Bureau of Economic Research.

Bartik, A. W., Z. B. Cullen, E. L. Glaeser, M. Luca, and C. T. Stanton (2020): "What Jobs are Being Done at Home During the Covid-19 Crisis? Evidence from Firm-Level Surveys," NBER Working Paper 27422.

Baum-Snow, N., and L. Han (2021): "The Microgeography of Housing Supply," Working Paper.

Behrens, K., S. Kichko, and J.-F. Thisse (2021): "Working from Home: Too Much of a Good Thing?," Working Paper.

Bick, A., and A. Blandin (2021): "Real Time Labor Market Estimates During the 2020 Coronavirus Outbreak," Working paper.

Bick, A., A. Blandin, and K. Mertens (2021): "Work from Home Before and After the COVID-19 Outbreak," Working paper.

Bloom, N., R. Han, and J. Liang (2022): "How Hybrid Work from Home Works Out," Working paper.

Bloom, N., J. Liang, J. Roberts, and Z. J. Ying (2015): "Does working from home work? Evidence from a Chinese experiment," *The Quarterly Journal of Economics*, 130(1), 165– 218.

Brueckner, J., M. E. Kahn, and G. C. Lin (2021): "A New Spatial Hedonic Equilibrium in the Emerging Work-from-Home Economy?," Working Paper 28526, National Bureau of Economic Research.

Brynjolfsson, E., J. J. Horton, A. Ozimek, D. Rock, G. Sharma, and H.-Y. TuYe (2020): "COVID-19 and Remote Work: An Early Look at US Data," NBER Working Paper 27344.

Card, D. (2009): "Immigration and Inequality," *American Economic Review*, 99(2), 1–21.

Couture, V., J. I. Dingel, A. Green, J. Handbury, and K. R. Williams (2021): “JUE Insight: Measuring movement and social contact with smartphone data: a real-time application to COVID-19,” *Journal of Urban Economics*.

CTPP (2016): Census Transportation Planning Products, American Association of State Highway and Transportation Officials. https://ctpp.transportation.org/ctpp-data-set-information/. Accessed September 2020.

Davis, M. A., A. C. Ghent, and J. M. Gregory (2022): “The Work-at-Home Technology Boon and its Consequences,” Working Paper 28461, National Bureau of Economic Research.

Davis, M. A., and F. Ortalo-Magné (2011): “Household Expenditures, Wages, Rents,” *Review of Economic Dynamics*, 14(2), 248 – 261.

De Fraja, G., J. Matheson, and J. Rockey (2021): “Zoomshock: The geography and local labour market consequences of working from home,” Working paper.

Delventhal, M. J., E. Kwon, and A. Parkhomenko (2022): “JUE Insight: How do cities change when we work from home?,” *Journal of Urban Economics*, 127, 103331, JUE Insights: COVID-19 and Cities.

Dingel, J. I., and B. Neiman (2020): “How Many Jobs Can Be Done at Home?,” *Journal of Public Economics*, 189, 104235.

Dingel, J. I., and F. Tintelnot (2020): “Spatial Economics for Granular Settings,” Working Paper.

Eeckhout, J., R. Pinheiro, and K. Schmidheiny (2014): “Spatial Sorting,” *Journal of Political Economy*, 122(3), 554 – 620.

Ellen, I. G., and K. Hempstead (2002): “Telecommuting and the Demand for Urban Living: A Preliminary Look at White-collar Workers,” *Urban Studies*, 39(4), 749–766.

Gaspar, J., and E. Glaeser (1998): “Information Technology and the Future of Cities,” *Journal of Urban Economics*, 43(1), 136–156.

Glaeser, E., and G. Ponzetto (2007): “Did the Death of Distance Hurt Detroit and Help New York?,” NBER Working Papers 13710, National Bureau of Economic Research, Inc.

Graham, M. R., M. J. Kutzbach, and B. McKenzie (2014): “Design Comparison of LODES and ACS Commuting Data Products,” Discussion Paper 14-38, U.S. Census Bureau Working Paper.

Gupta, A., J. Peeters, V. Mittal, and S. Van Nieuwerburgh (2021): “Flattening the Curve: Pandemic-Induced Revaluation of Urban Real Estate,” Working paper.

Gyourko, J., C. Mayer, and T. Sinai (2013): “Superstar Cities,” *American Economic Journal: Economic Policy*, 5(4), 167–99.

Haslag, P. H., and D. Weagley (2021): “From L.A. to Boise: How Migration Has Changed During the COVID-19 Pandemic,” Working paper.

Heblich, S., S. J. Redding, and D. M. Sturm (2020): “The Making of the Modern Metropolis: Evidence from London,” *Quarterly Journal of Economics*, 135(4), 2059–2133.

Katz, L., and K. M. Murphy (1992): “Changes in Relative Wages, 1963–1987: Supply and Demand Factors,” *The Quarterly Journal of Economics*, 107(1), 35–78.

Kyriakopoulou, E., and P. M. Picard (2021): “The Zoom City: Working From Home and Urban Land Structure,” Working paper.

Larson, W., and W. Zhao (2017): “Telework: Urban form, energy consumption, and greenhouse gas implications,” *Economic Inquiry*, 55(2), 714–735.

Lee, E. (2020): “Trade, inequality, and the endogenous sorting of heterogeneous workers,” *Journal of International Economics*, 125, 103310.

Lennox, J. (2020): “More working from home will change the shape and size of cities,” Working Paper.

Li, W., and Y. Su (2021): “The Great Reshuffle: Residential Sorting During the COVID-19 Pandemic and Its Welfare Implications,” Working paper.

Liu, S., and Y. Su (2021): “The impact of the COVID-19 pandemic on the demand for density: Evidence from the U.S. housing market,” *Economics Letters*, 207, 110010.

LODES(2016): LongitudinalEmployer-HouseholdDynamicsOrigin-DestinationEmployment Statistics, U.S. Census Bureau. https://lehd.ces.census.gov/data/. Accessed September 2020.

Mas, A., and A. Pallais (2017): “Valuing alternative work arrangements,” *American Economic Review*, 107(12), 3722–59.

Mas, A., and A. Pallais (2020): “Alternative Work Arrangements,” *Annual Review of Economics*.

Mongey, S., L. Pilossoph, and A. Weinberg (2020): “Which Workers Bear the Burden of Social Distancing?,” Working Paper 27085, National Bureau of Economic Research.

Monte, F., S. J. Redding, and E. Rossi-Hansberg (2018): “Commuting, Migration, and Local Employment Elasticities,” *American Economic Review*, 108(12), 3855–90.

Moretti, E. (2012): *The New Geography of Jobs*. Houghton Mifflin Harcourt, New York.

NHTS (2017): National Household Transportation Survey, Federal Highway Administration, U.S. Department of Transportation. https://nhts.ornl.gov/ Accessed May 2021.

Ozimek, A. (2020): “Remote Workers on the Move,” Upwork Economist Report.

Ramani, A., and N. Bloom (2021): “The Donut Effect of Covid-19 on Cities,” Working Paper 28876, National Bureau of Economic Research.

Rhee, H.-J. (2008): “Home-based telecommuting and commuting behavior,” *Journal of Urban Economics*, 63(1), 198–216.

Rosenthal, S. S., W. C. Strange, and J. A. Urrego (2021): “JUE insight: Are city centers losing their appeal? Commercial real estate, urban spatial structure, and COVID-19,” *Journal of Urban Economics*, p. 103381.

Safirova, E. (2003): “Telecommuting, traffic congestion, and agglomeration: a general equilibrium model,” *Journal of Urban Economics*, 52(1), 26–52.

Saiz, A. (2010): “The Geographic Determinants of Housing Supply*,” *The Quarterly Journal of Economics*, 125(3), 1253–1296.

SIPP (2018): Survey of Income and Program Participation, U.S. Census Bureau. https://www.census.gov/programs-surveys/sipp/data/datasets/2018-data/2018.html. Accessed September 2020.

Spear, B. D. (2011): *NCHRP 08-36, Task 098 Improving Employment Data for Transportation Planning*. American Association of State Highway and Transportation Officials.

Stanton, C. T., and P. Tiwari (2021): “Housing Consumption and the Cost of Remote Work,” Working Paper 28483, National Bureau of Economic Research.

Tsivanidis, N. (2019): “The Aggregate and Distributional Effects of Urban Transit Infrastructure: Evidence from Bogotá’s TransMilenio,” Working Paper.

Valentinyi, A., and B. Herrendorf (2008): “Measuring factor income shares at the sectoral level,” *Review of Economic Dynamics*, 11(4), 820–835.

Zhu, P. (2012): “Are telecommuting and personal travel complements or substitutes?,” *The Annals of Regional Science*, 48(2), 619–639.

Appendix

A. Data

This appendix section describes the data. The data can be accessed at https://doi.org/10.7910/DVN/IJSQEY, and should be cited as follows:

> Parkhomenko, Andrii, 2022, "Data for: Spatial Implications of Telecommuting in the United States", https://doi.org/10.7910/DVN/IJSQEY, Harvard Dataverse, V1, UNF:6:xSQvklXUQ5I198Il6kAltA== [fileUNF]

A.1. Telecommuting Frequencies

To study the frequency of working from home for individuals in various industries and education levels, we use the data from the 2018 Survey of Income and Program Participation (SIPP). The survey asks how many full paid work days a survey respondent worked in a reference week. We focus our analysis on full-time workers 16 years or older who are not self-employed. Our estimates are based on a final sample of 261,757 observations.

A.2. Work-from-Home Wage Premia

We estimate differences between the wages of telecommuters and non-telecommuters from the 2012–2016 ACS. We identify those who work from home full time as individuals who responded to the question about means of transportation to work as “worked at home.” For workers with telecommutable occupations only, for each industry/education category separately, we regress log hourly wages on a dummy variable for working from home full time, controlling for age, sex, race, industry, occupation, and PUMA of residence. Our sample includes a total of 4.7 million observations.

A.3. Local Wages Indices

Our sources of wage data is the Census Transportation Planning Products (CTPP), aggregated at the Census tract level, and microdata from the American Community Survey (ACS). We use the data reported for the period from 2012 to 2016. We use the variable “earnings in the past 12 months (2016 $), for the workers 16-year-old and over,” which is based on the respondents’ workplace locations. The variable provides the estimates of the number of people in each of the several earning bins in each workplace tract.[46]

We calculate mean labor earnings for tract k as $\bar{w}_k = \left(\sum_b N_{b,k}\bar{w}_b\right)/\sum_b N_{b,k}$, where $N_{b,k}$ is the number of workers in bin b in tract k, and $\bar{w}_b$ is mean earnings in bin b for each PUMA,

[46] The bins are $\leq$ $9,999; $10,000–$14,999; $15,000–$24,999; $25,000–$34,999; $35,000–$49,999; $50,000–$64,999; $65,000–$74,999; $75,000–$99,999; and $\geq$ $100,000.

calculated from the ACS microdata. Next, to control for possible effects of workers' heterogeneity on tract-level averages, we estimate

$$\bar{w}_k = \alpha + \beta_1 age_k + \beta_2 sexratio_k + \sum_r \beta_{2,r} race_{r,k} + \sum_d \beta_{3,d} ind_{d,k} + \sum_o \beta_{4,o} occ_{o,k} + \epsilon_k, \quad \text{(A.1)}$$

where age_k is the average age of workers; $sexratio_k$ is the proportion of males to females in the labor force; $race_{r,j}$ is the share of race $r \in \{Asian, Black, Hispanic, White\}$; $ind_{d,k}$ is the share of jobs in industry d; and $occ_{o,k}$ is share of jobs in occupation o in tract k.[47] The estimated tract-level wage index is the sum of the estimated constant and the tract fixed effect: $\hat{w}_k^0 \equiv \hat{\alpha} + \hat{\epsilon}_k$. We then construct wage indices for each location j, $\hat{w}_j^0$, as the employment-weighted average of the values of $\hat{w}_k^0$ for each tract k that pertains to model location j.

Then, using microdata from the American Community Survey (ACS), we calculate average wage premia for college over non-college workers, and tradable industry over non-tradable industry workers, separately at the place-of work public-use microdata area (POWPUMA) level, and assume that they are uniform across all model locations belonging to a single POWPUMA.[48] Let the college wage premium for model location j be designated ϕ_j^H, and for the sake of concision of presentation let us also define a non-college wage "premium" $\phi_j^L = 1$ that is normalized to 1. Let the tradable industry premium for model location j be defined as ρ_j^G, while the non-tradable premium $\rho_j^S = 1$ is normalized to 1.

For each location j, we need the two sets of conditions to hold. First, the relationships between the wages paid to different education and industry categories implied by the "premia" we have just defined: $\hat{w}_{mj}^s / \hat{w}_{m'j}^{s'} = \left(\phi_j^s \rho_j^m\right) / \left(\phi_j^{s'} \rho_j^{m'}\right)$ for $s, s' \in \{H, L\}$ and $m, m' \in \{G, S\}$. Second, we need the average wage to match the one derived from the data, given the relative prevalence of each type of worker: $\sum_s \sum_m \hat{w}_{mj}^s \pi_{mj}^s = \hat{w}_j^0$, where conditional choice probabilities $\pi_{mj}^s \equiv \sum_i \sum_o \pi_{mij}^{so}$, reflecting the total number of workers of each education level and industry with jobs in j, from all residence locations and occupations, are constructed as follows: we observe $\pi_{mj} \equiv \sum_s \sum_i \sum_o \pi_{mij}^{so}$ for each location, and observe $\pi_{m0}^s \equiv \sum_i \sum_j \sum_o \pi_{mij}^{so}$ at the economy-wide level, and assume that the educational composition of industry does not vary by location: $\pi_{mj}^s = \pi_{mj} \pi_{m0}^s$.

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[47] We use the following *industry* categories: Agricultural; Armed force; Art, entertainment, recreation, accommodation; Construction; Education, health, and social services; Finance, insurance, real estate; Information; Manufacturing; Other services; Professional scientific management; Public administration, Retail. We use the following *occupation* categories: Architecture and engineering; Armed Forces; Arts, design, entertainment, sports, and media; Building and grounds cleaning and maintenance; Business and financial operations specialists; Community and social service; Computer and mathematical; Construction and extraction; Education, training, and library; Farmers and farm managers; Farming, fishing, and forestry; Food preparation and serving related; Healthcare practitioners and technicians; Healthcare support; Installation, maintenance, and repair; Legal; Life, physical, and social science; Management; Office and administrative support; Personal care and service; Production; Protective service; Sales and related.

[48] POWPUMAs are larger than PUMAs and even in dense urban areas often correspond to counties.

Manipulating these two sets of conditions, we can calculate $\widehat{w}_{mj}^{s}$ in the following way. First, the average wage for college-educated tradable workers, as a function of $\widehat{w}_{j}^{0}$:

$$\widehat{w}_{Gj}^{H} = \frac{\widehat{w}_{j}^{0}}{\sum_s \sum_m \frac{\phi_j^s \rho_j^m}{\phi_j^H \rho_j^G} \sum_i \sum_o \pi_{mij}^{so}}. \tag{A.2}$$

Then, wages for each category $s \in \{H, L\}$ and $m \in \{G, S\}$ are given by $\widehat{w}_{mj}^{s} = \frac{\phi_j^s \rho_j^m}{\phi_j^H \rho_j^G} \widehat{w}_{Gj}^{H}$. These are then translated into wages in the model w_{mj}^{s}, according to the following equation:

$$w_{mj}^{s} = \frac{\left(\widehat{w}_{mj}^{s}\right)^{\alpha}}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}} \left(\frac{\sum_i \sum_o \pi_{mij}^{so}}{\sum_i \sum_o \pi_{mij}^{so} \Omega_{mij}^{so}}\right)^{\alpha}. \tag{A.3}$$

A.4. Telecommuters' Distance to Job Sites

To study the relationship between the propensity to work at home and the distance between home and job site, we use data from the 2017 National Household Transportation Survey (NHTS). We focus on full time workers in the 48 contiguous United States and Washington, D.C. Bins for each commuting frequency are constructed as follows: 5 days per week telecommuters reported working from home more than 90% of the days in a 21.67-day average work month; 4 days—between 90% and 70%, 3 days—between 70% and 50%, etc. The sample comprises 83,512 observations. The distance between home and job site is great circle distance as reported in the database. Those who reported working from home over 22 days a month are excluded.

A.5. Local Rent Indices

We measure local rents by constructing hedonic rent indices at the level of PUMAs as in Eeckhout, Pinheiro, and Schmidheiny (2014). In cases when a PUMA contains more than one model location we assign the same index to all. We use the 2016 5-year ACS sample tabulated by the IPUMS (ACS, 2016)[49] To construct local rent indices, we use self-reported rents and estimate the following regression,

$$\ln q_{\iota,it} = \beta_0 + \boldsymbol{\beta}_1 \mathcal{X}_{\iota,it} + \varphi_i + \varphi_t + \varepsilon_{\iota,it}, \tag{A.4}$$

where $q_{\iota,it}$ is the rent reported by household ι in PUMA i and year t, while $\mathcal{X}_{\iota,it}$ is a vector of controls that includes the number of rooms in the dwelling, the number of units in the structure (e.g., single-family detached, 2-family building), and the year of construction. Parameters φ_i and φ_t are PUMA and year fixed effects, respectively, and $\varepsilon_{\iota,it}$ is the error term. The rent index, Q_i, represents the rent after controlling for the observable characteristics listed before and idiosyncratic effects, and is given by $Q_i \equiv \exp(\beta_0 + \varphi_i)$.

[49] We keep only household heads to ensure that the analysis is at the level of a residential unit. We exclude observations who live in group quarters; live in farm houses, mobile homes, trailers, boats, tents, etc.; are younger than 18 years old; and live in a dwelling that has no information on the year of construction.

A.6. Estimation of Travel Times

We follow the practice recommended by Spear (2011) and use LODES data as a measure of commuting flows and Census Transportation Planning Products (CTPP) data to provide information on commute times. The CTPP database reports commuting time data for origin-destination pairs of Census tracts across the contiguous United States for 2012–2016, and is tabulated using American Community Survey (ACS) data.[50] Travel times are reported for a little over 4 million trajectories, a small fraction of all possible bilateral trajectories, because most pairs of tracts are far enough apart that the ACS survey does not observe anyone commuting between them. We process this data in the following steps.

First, we calculate average travel time between each pair of locations as the average of all tract-to-tract times with an origin inside one location and a destination in the other. We throw out the calculation for any pair for which less than 10% of all possible tract-to-tract times is reported by CTPP. We also exclude times that imply a speed of more than 100 km/hour or less than 5 km/hour. We perform this same calculation for average distance of each location *from itself*, obtaining data-based estimates of internal travel time for each location.

Second, to prevent "breaks" in the network, we check to see if any location does not have an estimated travel time to its 5 nearest neighbors. If any are missing, we project a one using estimated coefficients of a regression of average location-to-location travel times on average great circle distance and an indicator of origin = destination. This procedure adds ≈10,000 additional links, out of 20,268,004 possible location-to-location trajectories.

Finally, we take the ≈34,000 primitive connections, the travel times for which we have calculated as detailed above, as the first-order connections in a transport network. We use Dijkstra's algorithm to find the least possible travel times through this network between each pair of model locations.

A.7. Safegraph Location Data

Safegraph tracks and collects information from approximately 20 million of mobile devices in the US, and uses this information to construct geographical location data. Home locations are determined based on where mobile devices are detected at nighttime. To obtain an estimate of the change in the residence patterns between 2019 and 2021, we take the number of devices resident in each Census block group in both December 2019 and December 2021. We aggregate these counts up to the level of model locations, and calculate the share of devices in each location. Finally we calculate the log of the difference in these shares for each location over time.

How accurate is the Safegraph data as a proxy of local population? Couture, Dingel, Green, Handbury, and Williams (2021) show that cell phone data provides reliable estimates of local

[50] The CTPP data divides commuting times into 10 bins: less than 5 minutes, 5 to 14 minutes, 15 to 19 minutes, 20 to 29 minutes, 30 to 44 minutes, 45 to 59 minutes, 60 to 74 minutes, 75 to 89 minutes, 90 or more minutes, and work from home.

population levels at the county level. To assess the validity of Safegraph data at the level of our model locations which are typically smaller than counties, we compute population estimates for each location using Census estimates at the tract level for the year 2019. Similarly, for each location we compute the number of mobile devices. Figure A. 1 shows that the correlation between Safegraph and Census population estimates is nearly one. At the same time, the regression coefficient of slightly lower than one suggests that Safegraph somewhat oversamples locations with larger population.

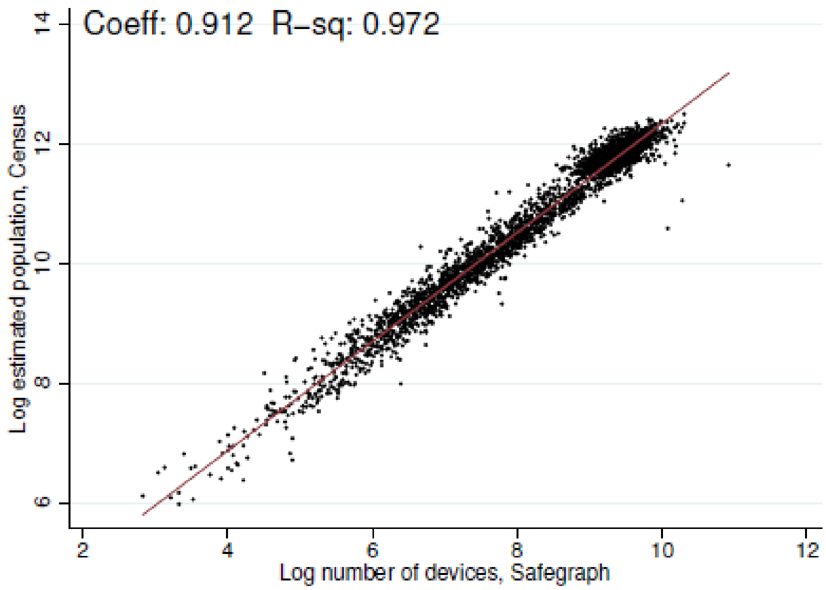

Figure A. 1. Comparison of Census and Safegraph population counts

Note: The figure shows the relationship between population estimates for each model location based on the Census data and the number of mobile devices in each location from the Safegraph data in 2019.

B. Existence and Uniqueness of an Equilibrium

Consider a simplified version of our model with fixed floorspace supply, single industry, no heterogeneity in education, and no externalities in residential amenities. Also, let all workers have an occupation that allows telecommuting. Without telework, this model corresponds to a version of Ahlfeldt, Redding, Sturm, and Wolf (2015) for which Allen, Arkolakis, and Li (2020) derive sufficient conditions for existence and uniqueness.

The simplified model's equilibrium can be written as a system of $I \times 3$ equations in floorspace prices, supply of on-site work days, and productivity as

$$q_i^{1+\gamma\epsilon} = \sum_{j\in\mathcal{J}} \frac{\gamma}{\bar{H}_{Ri}} \Phi^{-1/\epsilon} B_{ij}^{\epsilon} \widetilde{\mathbb{Q}}_{ij}^{-\epsilon} \mathbb{Q}_{ij}^{\frac{1+\epsilon(1+\alpha(\zeta-1))}{\alpha(\zeta-1)}} \bar{\alpha}^{1+\epsilon} A_j^{\frac{1+\epsilon}{\alpha}}, \tag{B.1}$$

$$N_{WCi} = \sum_{j\in\mathcal{J}} q_i^{-(1-\alpha)(\zeta-1)} q_j^{-\gamma\epsilon} \Phi^{-1/\epsilon} B_{ji}^{\epsilon} \widetilde{\mathbb{Q}}_{ji}^{-\epsilon} \mathbb{Q}_{ji}^{\frac{\epsilon+\alpha(\epsilon-1)(\zeta-1)}{\alpha(\zeta-1)}} \bar{\alpha}^{\epsilon} A_i^{\frac{\epsilon}{\alpha}}, \tag{B.2}$$

$$A_i = a_i \left(\frac{N_{WCi}}{\Lambda_i}\right)^{\lambda}, \tag{B.3}$$

where $\overline{H}_{Ri}$ is the exogenous supply of residential floorspace and $\Phi^{1/\epsilon}$ is expected utility. Let $\mathbb{Q}_{ij}^1 \equiv q_j^{-(1-\alpha)(\zeta-1)}$, $\widetilde{\mathbb{Q}}_{ij}^1 \equiv \mathbb{Q}_{ij}^1 e^{\kappa t_{ij}}$, and $\mathbb{Q}_{ij}^2 = \nu^{\zeta-1} q_i^{-(1-\alpha)(\zeta-1)} e^{\kappa t_{ij}(1+\alpha(\zeta-1))}$, as well as $\mathbb{Q}_{ij} \equiv \mathbb{Q}_{ij}^1 + \mathbb{Q}_{ij}^2$ and $\widetilde{\mathbb{Q}}_{ij} \equiv \widetilde{\mathbb{Q}}_{ij}^1 + \mathbb{Q}_{ij}^2$.

Note that the system (1)–(3) has the form of system (1) in Allen, Arkolakis, and Li (2020) and can be written as $\mathcal{X}_{ih} = \sum_{j \in \mathcal{J}} \mathcal{F}_{ijh}(\mathcal{X}_{j1}, \ldots, \mathcal{X}_{jH})$, where h refers to an interaction of a particular type. In our case, there are 3 interactions with $\mathcal{X}_{j1} = q_j$, $\mathcal{X}_{j2} = N_{WCj}$, and $\mathcal{X}_{j3} = A_j$. Let $\mathcal{E}_{ij}(\mathcal{X}_h \mathcal{X}_{h'}) \equiv \partial \ln \mathcal{F}_{ijh} / \partial \ln \mathcal{X}_{jh'}$. Using results from Allen,
Arkolakis, and Li (2020), we can study existence and uniqueness by studying the properties of the 3×3 matrix where each component is given by $\max_{i,j}\{|\mathcal{E}_{ij}(\mathcal{X}_h \mathcal{X}_{h'})|\}$.

Because effective effort and commuting costs include additive terms, two out of nine cross-elasticities that form the above-mentioned matrix are location-specific:

$$\mathcal{E}_{ij}(q, q) = \frac{1-\alpha}{1+\gamma\epsilon}\left[\epsilon(\zeta-1)\frac{\widetilde{\mathbb{Q}}_{ij}^1}{\widetilde{\mathbb{Q}}_{ij}} - \frac{1+\epsilon(1+\alpha(\zeta-1))}{\alpha}\frac{\mathbb{Q}_{ij}^1}{\mathbb{Q}_{ij}}\right], \tag{B.4}$$

$$\mathcal{E}_{ij}(N_{WC}, q) = \begin{cases} \frac{1-\alpha}{1+\gamma\epsilon}\left[\epsilon(\zeta-1)\frac{\mathbb{Q}_{ji}^2}{\widetilde{\mathbb{Q}}_{ji}} - \frac{\epsilon+\alpha(\epsilon-1)(\zeta-1)}{\alpha}\frac{\mathbb{Q}_{ji}^2}{\mathbb{Q}_{ji}}\right] - \frac{\gamma\epsilon}{1+\gamma\epsilon} & \text{if} j \neq i, \\ \frac{1-\alpha}{1+\gamma\epsilon}\left[\epsilon(\zeta-1)\frac{\widetilde{\mathbb{Q}}_{ji}^1}{\widetilde{\mathbb{Q}}_{ji}} - \frac{\epsilon+\alpha(\epsilon-1)(\zeta-1)}{\alpha}\frac{\mathbb{Q}_{ji}^1}{\mathbb{Q}_{ji}}\right] - \frac{\gamma\epsilon+(1-\alpha)(\zeta-1)}{1+\gamma\epsilon} & \text{if} j = i. \end{cases} \tag{B.5}$$

That is, existence and uniqueness may depend on location-specific outcomes; however, we can check the domain of $\{\widetilde{\mathbb{Q}}_{ij}^1/\widetilde{\mathbb{Q}}_{ij}, \mathbb{Q}_{ij}^1/\mathbb{Q}_{ij}, \mathbb{Q}_{ji}^2/\widetilde{\mathbb{Q}}_{ji}, \mathbb{Q}_{ji}^2/\mathbb{Q}_{ji}\}$ to obtain maximum absolute values of (4) and (5), given values of α, γ, ϵ, ζ, λ, κ, and ν from our calibrated model (see Tables 3 and 5).[51] We do so by noticing that $t_{ij} \in [0, \infty)$ and $q_i \in (0, \infty)$. Thus, the matrix of cross-elasticites $\max_{i,j}\{|\mathcal{E}_{ij}(\mathcal{X}_h \mathcal{X}_{h'})|\}$ for $h \in \{q, N_{WC}, A\}$ is

$$\mathcal{A} \equiv \begin{bmatrix} \frac{1-\alpha}{1+\gamma\epsilon}\frac{1}{1+\nu^{\zeta-1}}\left[\frac{1+\epsilon(1+\alpha(\zeta-1))}{\alpha} - \epsilon(\zeta-1)\right] & 0 & \frac{1+\epsilon}{\alpha} \\ \frac{1-\alpha}{1+\gamma\epsilon}\frac{1}{1+\nu^{\zeta-1}}\left[\frac{\epsilon+\alpha(\epsilon-1)(\zeta-1)}{\alpha} - \epsilon(\zeta-1)\right] + \frac{\gamma\epsilon+(1-\alpha)(\zeta-1)}{1+\gamma\epsilon} & 0 & \frac{\epsilon}{\alpha} \\ 0 & \lambda & 0 \end{bmatrix} \tag{B.6}$$

Existence and uniqueness. According to Theorem 1 in Allen, Arkolakis, and Li (2020), if $\mathcal{A}$ has a spectral radius less than 1, then the equilibrium exists and is unique. For the parameter values in our calibrated model, the spectral radius of $\mathcal{A}$ is 1.0084, marginally greater than 1. That is, in the simplified version of our model the equilibrium is not guaranteed to exist and, if it does, multiple equilibria exist.

[51] Our calibrated model has multiple values of ν and ζ depending on education and industry. We use weighted-average values of each parameter.

How does this finding compare to the result of Allen, Arkolakis, and Li (2020) for a model without telework? They find that, as long as the productive externality is weak enough, $\lambda < \min\left\{1-\alpha, \frac{\alpha}{1+\epsilon}\right\}$, the equilibrium is unique. In our model, $\lambda = 0.086$ and $\min\left\{1-\alpha, \frac{\alpha}{1+\epsilon}\right\} = 0.162$. That is, if our simplified model did not have work from home, the externality would be weak enough to yield uniqueness.

Why does the introduction of the ability to substitute on-site and remote work result in multiple equilibria? In a standard model, the extent to which a location with high exogenous productivity attracts workers is amplified via agglomeration externalities but, in turn, is dampened as the number of workers willing to commute there daily is limited. Work from home expands the firm market access (or "catchment area") in such locations so they can attract more workers because they do not have to commute daily. As a result, even modest values of λ can lead to multiple equilibria.

To confirm this reasoning, we found that when $\lambda < 0.084$, the spectral radius of $\mathcal{A}$ is less than 1. We also shut down the ability to telecommute by setting $\zeta = 0$ and $\nu = 0$. In this case, even with $\lambda = 0.086$, the spectral radius is 0.82, and there exists a unique equilibrium. Since we assumed that in this version of the model all workers can telecommute, even though in the data only 34% of workers can work remotely, the latter result is highly relevant and, all else equal, makes the uniqueness of an equilibrium in our quantitative model a likely outcome.

C. Model Inversion and Calibration

C.1. Inversion and Calibration Algorithm

In order to obtain the values of location-specific fundamentals $\tilde{a}_{mi} \equiv a_{mi}\Lambda_i^{-\lambda}$, $\tilde{x}_{mi}^s \equiv x_{mi}^s\Lambda_i^{-\chi}$, $\tilde{\phi}_i \equiv \phi_i\Lambda_i$, X_{mi}, X_i^s, E_{mj}, E_j^s, and ω_{mj}, as well as economy-wide parameters ν_m^s, ς_m^s, ζ_m^s, τ, and β, we invert the model using the following sequence of steps.

1. Guess the values of X_{mi}, X_i^s, E_{mj}, E_j^s, ν_m^s, ς_m^s, ζ_m^s, τ, and β.

2. Perform the following sequence:

   (a) Solve for industry and location choice probabilities, π_{mij}^{so}, using equation (3.3) and compute residential population and employment by education and industry as follows: $N_{Rmi} = \sum_s \sum_o \sum_j \pi_{mij}^{so}$, $N_{Ri}^s = \sum_o \sum_m \sum_j \pi_{mij}^{so}$, $N_{Wmj} = \sum_s \sum_o \sum_i \pi_{mij}^{so}$, and $N_{Wj}^s = \sum_o \sum_m \sum_i \pi_{mij}^{so}$.

   (b) Solve for optimal commuting frequency, θ_{mij}^{so}, using equation (3.13) and find the average for each (m,s) type: $\bar{\theta}_m^s \equiv \left(\sum_o \sum_i \sum_j \pi_{mij}^{so}\theta_{mij}^{so}\right)/\left(\sum_o \sum_i \sum_j \pi_{mij}^{so}\right)$.

   (c) Compute the variance of commuting frequencies for each (m,s) for the interval $\theta \in [0.2,0.8]$: $\mathrm{Var}(\theta_s^m | \theta \in [0.2,0.8])$.

(d) Compute the average distance between residence and job site for "commuters" ($\theta > 0.9$) and "telecommuters" ($\theta \leq 0.9$), and then calculate the ratio of the two numbers.

(e) Solve for optimal effort Ω_{mij}^{so} and commuting costs, as a function of optimal commuting frequency, d_{mij}^{so}, using equations (3.11) and (3.12), respectively.

(f) Solve for wages and disposable income: (i) convert wages observed in the tradable sector in the data to the measure of wages used in the model using equation (A.3); (ii) find disposable income using equation (3.12). [52]

(g) Combine equations (3.16) and (3.19) to find ω_{mj}:

$$\omega_{mj} = \left[1 + \left(\frac{w_{mj}^{H}}{w_{mj}^{L}}\right)^{\frac{1+\alpha(\xi-1)}{\alpha\xi}} \left(\frac{\sum_o \sum_i \pi_{mij}^{Lo} \Omega_{mij}^{Lo}}{\sum_o \sum_i \pi_{mij}^{Ho} \Omega_{mij}^{Ho}}\right)^{\frac{1}{\xi}}\right]^{-1} \tag{C.1}$$

(h) Solve for labor productivity in the non-tradable sector using the data on prices of non-tradables and equation (3.22).

(i) Compute the ratio between mean wages in tradable/non-tradable sectors.

(j) Compute for each industry/education pair the ratio between mean wages for telecommutable workers with $\theta > 0.8$, and those with $\theta < 0.2$.

(k) Update $\bar{X}_{mi}$, $\bar{X}_i^s$, $\bar{E}_{mj}$, $\bar{E}_j^s$: increase $\bar{X}_{mi}$ if the value of N_{Rmi} in the model is lower than in the data, reduce it otherwise; increase $\bar{X}_i^s$ if the value of N_{Ri}^s in the model is lower than in the data, reduce it otherwise; increase $\bar{E}_{mj}$ if the value of N_{Wmj} in the model is lower than in the data, reduce it otherwise; increase $\bar{E}_j^s$ if the value of N_{Wj}^s in the model is lower than in the data, reduce it otherwise.

(l) Update the WFH aversion ς_m^s: increase ς_m^s if the average θ of type (m, s) in the data is greater than the value of $\bar{\theta}_m^s$; reduce ν_m^s otherwise.

(m) Update the WFH productivity ν_m^s: increase ν_m^s if the wage ratio between telecommutable workers with $\theta < 0.1$ to those with $\theta > 0.9$ is lower than the wage gap between those who work from home full-time to those who commute full time in the data; reduce ν_m^s otherwise.

[52] As discussed in Section C.2, our model is overidentified because employment amenities determine both local employment by industry and education and the college wage premium in the non-tradable sector. Thus, we take wages in the tradable sector directly from the data, while wages in the non-tradable sector are determined within the model.

(n) Update τ: increase τ if the ratio of average distance between residence and job site for "commuters" to "telecommuters" is higher in the model than its data counterpart; reduce τ otherwise.

(o) Update the non-tradables expenditure share β: increase β if the ratio between mean wages in tradable/non-tradable sectors is lower in the model than in the data; decrease β otherwise.

(p) Return to step (2a) and repeat the sequence, unless moments computed in steps (2a), (2b), (2c), (2d), (2i), and (2j) in the model are equal to their counterparts in the data within a tolerance limit.

3. Construct education-industry amenities as $X_{mi}^{s} = X_{mi}X_i^s$ and $E_{mj}^{s} = E_{mj}E_j^s$.

4. Compute the exogenous part of amenities, $\tilde{x}_{mi}^{s} \equiv x_{mi}^{s}\Lambda_i^{-\chi}$, using equation (3.27) as follows: $\tilde{x}_{mi}^{s} = X_{mi}^{s}/(N_{Ri})^{\chi}$, where N_{Ri} and N_{WTj} are constructed using probabilities computed in step (2a).

5. Compute the exogenous part of productivity, $\tilde{a}_{mi} \equiv a_{mi}\Lambda_i^{-\lambda}$, using equation (3.26) as follows: $\tilde{a}_{mi} = A_{mj}/\left(N_{WCj} + \psi N_{WTj}\right)^{\lambda}$, where N_{WCj} and N_{WTj} are constructed from choice probabilities computed in step (2a), and commuting frequencies computed in step (2b). Figure J.6 shows calibrated values of A_{mj} on a map.

6. Compute floorspace demand H_i and then compute construction sector productivities, $\tilde{\phi}_i \equiv \phi_i\Lambda_i$, using equations (3.24) and (3.25) as follows: $\tilde{\phi}_i = H_i q_i^{-\frac{1}{\eta_i}}(1-\eta_i)^{-\frac{1-\eta_i}{\eta_i}}$.

C.2. Proof of Proposition 1: Existence and Uniqueness of model Inversion

In what follows we prove that there exists a unique set of parameters consistent with the data being an equilibrium of the model.[53] These parameters are $\tilde{a}_{mi} \equiv a_{mi}\Lambda_i^{-\lambda}$, $\tilde{x}_{mi}^{s} \equiv x_{mi}^{s}\Lambda_i^{-\chi}$, $\tilde{\phi}_i \equiv \phi_i\Lambda_i$, X_{mi}, X_i^s, E_{mj}, E_j^s, and ω_{mj}.

Existence and uniqueness of employment amenities. Recall that we assume that employment amenities can be split into an education- and an industry-specific component as $E_{mj}^{s} = E_{mj}E_j^s$. Note that once the markets for non-college and college labor, as well as labor in the non-tradable industry clear, the market for labor in the tradable industry will clear as well. Thus, we

[53] The proof follows closely Ahlfeldt, Redding, Sturm, and Wolf (2015) (see Propositions S.3 and S.4 in their appendix) but requires extra steps due to the nature of our model and data. When appropriate, we refer to lemmas and equations in their proof.

can normalize $E_{Gj} = 1$ for all j. Define composite employment amenities as a function of amenities per se and wages:

$$\hat{E}_{mj}\hat{E}_j^s = E_{mj}E_j^s w_{mj}^s. \tag{C.2}$$

In equilibrium, these three labor market clearing conditions must hold in each location:

$$D_{Wj}^L\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right) \equiv N_{Wj}^L - \sum_i N_{Ri}^L \sum_o \left[\frac{\left(\hat{E}_{Sj}\hat{E}_j^L \Phi_{Sij}^{Lo}\right)^\epsilon}{\sum_{j'}\left(\hat{E}_{Sj'}\hat{E}_{j'}^L \Phi_{Sij'}^{Lo}\right)^\epsilon} n_{RSi}^{Lo} + \frac{\left(\hat{E}_j^L \Phi_{Gij}^{Lo}\right)^\epsilon}{\sum_{j'}\left(\hat{E}_{j'}^L \Phi_{Gij'}^{Lo}\right)^\epsilon} n_{RGi}^{Lo}\right] = 0, \tag{C.3}$$

$$D_{Wj}^H\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right) \equiv N_{Wj}^H - \sum_i N_{Ri}^H \sum_o \left[\frac{\left(\hat{E}_{Sj}\hat{E}_j^H \Phi_{Sij}^{Ho}\right)^\epsilon}{\sum_{j'}\left(\hat{E}_{Sj'}\hat{E}_{j'}^H \Phi_{Sij'}^{Ho}\right)^\epsilon} n_{RSi}^{Ho} + \frac{\left(\hat{E}_j^H \Phi_{Gij}^{Ho}\right)^\epsilon}{\sum_{j'}\left(\hat{E}_{j'}^H \Phi_{Gij'}^{Ho}\right)^\epsilon} n_{RGi}^{Ho}\right] = 0, \tag{C.4}$$

$$D_{WSj}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right) \equiv N_{WSj} - \sum_i N_{RSi} \sum_o \left[\frac{\left(\hat{E}_{Sj}\hat{E}_j^L \Phi_{Sij}^{Lo}\right)^\epsilon}{\sum_{j'}\left(\hat{E}_{Sj'}\hat{E}_{j'}^L \Phi_{Sij'}^{Lo}\right)^\epsilon} n_{RSi}^{Lo} + \frac{\left(\hat{E}_{Sj}\hat{E}_j^H \Phi_{Sij}^{Ho}\right)^\epsilon}{\sum_{j'}\left(\hat{E}_{Sj'}\hat{E}_{j'}^H \Phi_{Sij'}^{Ho}\right)^\epsilon} n_{RSi}^{Ho}\right] = 0, \tag{C.5}$$

where $\Phi_{mij}^{so} \equiv \frac{1}{g_{ij}d_{mij}^{so}}\frac{\Omega_{mij}^{so}}{p_i^\beta q_i^\gamma}$ and $n_{Rmi}^{so} \equiv N_{Rmi}^{so}/N_{Rmi}$.[54] Note that d_{mij}^{so} and Ω_{mij}^{so} are functions of observed floorspace prices and the productivity of telework. Each of these conditions are of the form of the market clearing condition (S.43) in Ahlfeldt, Redding, Sturm, and Wolf (2015). Thus, using the same steps as in their Lemma S.6, we can show that function $D_{Wj}^s\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right)$ is continuous, homogeneous of degree zero, and exhibits gross substitution in $\hat{\mathbf{E}}^s$ for all $s \in \{L, H\}$. Similarly, function $D_{WSj}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right)$ is continuous, homogeneous of degree zero, and exhibits gross substitution in $\hat{\mathbf{E}}^S$. Moreover, $\sum_j D_{Wj}^s\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right) = 0$ and $\sum_j D_{WSj}\left(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right) = 0$ for all $s \in \{L, H\}$, $j \in \mathcal{J}$, and $\left\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right\} \in \mathbb{R}_+^I \times \mathbb{R}_+^I \times \mathbb{R}_+^I$.

Next, using the same steps as in Lemma S.7 in [?], we can demonstrate that, given the parameters $\{\epsilon, \kappa, \tau, \alpha, \zeta_m^s, \nu_m^s\}$ and observables $\{\mathbf{N}_{Wm}, \mathbf{N}_{Rm}, \mathbf{q}, \mathbf{p}, \mathbf{t}\}$: (1) conditional on $\hat{\mathbf{E}}_S$, there exists a unique vector $\hat{\mathbf{E}}^L$ that solves (3) for all j; (2) conditional on $\hat{\mathbf{E}}_S$, there exists a unique vector $\hat{\mathbf{E}}^H$ that solves (4) for all j; and (3) conditional on $\left\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H\right\}$, there exists a unique vector $\hat{\mathbf{E}}_S$ that solves (5) for all j. However, uniqueness of each vector of employment amenities conditional on another vector does not imply that the set of vectors $\left\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right\}$ consistent with labor market clearing is unique. In order to show that it is indeed unique, we employ a strategy similar to the first part of the proof of Lemma S.7 in Ahlfeldt, Redding, Sturm, and Wolf (2015).

Lemma C.1 Given the parameters $\{\epsilon, \kappa, \tau, \alpha, \zeta_m^s, \nu_m^s, \varsigma_m^s\}$ observables $\{\mathbf{N}_{Wm}, \mathbf{N}_{Rm}, \mathbf{q}, \mathbf{p}, \mathbf{t}\}$, there exist a unique set of vectors $\left\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\right\}$ such that conditions (3), (4), and (5) hold for all j.

[54] Even though employment shares n_{Rmi}^{so} are unobserved, their presence does not change the properties of market clearing conditions that are required for the set of employment amenities to exist and be unique.

Proof. The existence of $\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\}$ is guaranteed by the existence of each separate vector $\hat{\mathbf{E}}^L$, $\hat{\mathbf{E}}^H$, and $\hat{\mathbf{E}}_S$ that solves equations (C.3), (C.4), and (C.5), respectively, that we established above. Below we show that this set is also unique.

Denote by $D_W(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S)$ a stacked $3I \times 1$ vector that is composed of $D^L_{Wj}(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S)$, $D^H_{Wj}(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S)$, and $D_{WSj}(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S)$ for all j. Suppose that there exist two sets $\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\}$ and $\{\tilde{\mathbf{E}}^L, \tilde{\mathbf{E}}^H, \tilde{\mathbf{E}}_S\}$ such that $\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\} \neq \{\tilde{\mathbf{E}}^L, \tilde{\mathbf{E}}^H, \tilde{\mathbf{E}}_S\}$, while $D_W(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S) = D_W(\tilde{\mathbf{E}}^L, \tilde{\mathbf{E}}^H, \tilde{\mathbf{E}}_S) = \mathbf{0}$. By homogeneity of degree zero, we can rescale each of $\tilde{\mathbf{E}}^L$, $\tilde{\mathbf{E}}^H$, and $\tilde{\mathbf{E}}_S$ such that $\tilde{E}^L_j \geq \hat{E}^L_j$, $\tilde{E}^H_j \geq \hat{E}^H_j$, and $\tilde{E}_{Sj} \geq \hat{E}_{Sj}$ for all j, whereas $\tilde{E}^L_i = \hat{E}^L_i$, $\tilde{E}^H_i = \hat{E}^H_i$, and $\tilde{E}_{Si} = \hat{E}_{Si}$ for some i. Next, consider adjusting $\{\tilde{\mathbf{E}}^L, \tilde{\mathbf{E}}^H, \tilde{\mathbf{E}}_S\}$ to $\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\}$ in $I-1$ steps. By gross substitution, the excess labor demand in location i cannot decrease in any step and must increase in at least one step. Therefore, $D^L_{Wi}(\tilde{\mathbf{E}}^L, \tilde{\mathbf{E}}^H, \tilde{\mathbf{E}}_S) > D^L_{Wi}(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S)$, $D^H_{Wi}(\tilde{\mathbf{E}}^L, \tilde{\mathbf{E}}^H, \tilde{\mathbf{E}}_S) > D^H_{Wi}(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S)$, and $D_{WSi}(\tilde{\mathbf{E}}^L, \tilde{\mathbf{E}}^H, \tilde{\mathbf{E}}_S) > D_{WSi}(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S)$, a contradiction. Thus, there exists a unique set of vectors $\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\}$ such that $D_W(\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S) = \mathbf{0}$.

Existence and uniqueness of residential amenities. We can also define the following labor market clearing conditions in terms of the number of residents:

$$D^L_{Rj}(\mathbf{X}^L, \mathbf{X}^H, \mathbf{X}_S) \equiv N^L_{Rj} - \sum_j N^L_{Wj} \sum_o \left[\frac{\left(X_{Si} X^L_i \Phi^{Lo}_{Sij}\right)^\epsilon}{\sum_{i'} \left(X_{Si'} X^L_{i'} \Phi^{Lo}_{Si'j}\right)^\epsilon} n^{Lo}_{WSj} + \frac{\left(X^L_i \Phi^{Lo}_{Gij}\right)^\epsilon}{\sum_{i'} \left(X^L_{i'} \Phi^{Lo}_{Gi'j}\right)^\epsilon} n^{Lo}_{WGj} \right] = 0, \tag{C.6}$$

$$D^H_{Rj}(\mathbf{X}^L, \mathbf{X}^H, \mathbf{X}_S) \equiv N^H_{Rj} - \sum_j N^H_{Wj} \sum_o \left[\frac{\left(X_{Si} X^H_i \Phi^{Ho}_{Sij}\right)^\epsilon}{\sum_{i'} \left(X_{Si'} X^H_{i'} \Phi^{Ho}_{Si'j}\right)^\epsilon} n^{Ho}_{WSj} + \frac{\left(X^H_i \Phi^{Ho}_{Gij}\right)^\epsilon}{\sum_{i'} \left(X^H_{i'} \Phi^{Ho}_{Gi'j}\right)^\epsilon} n^{Ho}_{WGj} \right] = 0, \tag{C.7}$$

$$D_{RSj}(\mathbf{X}^L, \mathbf{X}^H, \mathbf{X}_S) \equiv N_{RSj} - \sum_j N_{WSj} \sum_o \left[\frac{\left(X_{Si} X^L_i \Phi^{Lo}_{Sij}\right)^\epsilon}{\sum_{i'} \left(X_{Si'} X^L_{i'} \Phi^{Lo}_{Si'j}\right)^\epsilon} n^{Lo}_{WSj} + \frac{\left(X_{Sj} X^H_i \Phi^{Ho}_{Sij}\right)^\epsilon}{\sum_{i'} \left(X_{Si'} X^H_{i'} \Phi^{Ho}_{Si'j}\right)^\epsilon} n^{Ho}_{WSj} \right] =. \tag{C.8}$$

Then we could proceed exactly as above to show that there exists a unique set $\{\mathbf{X}^L, \mathbf{X}^H, \mathbf{X}_S\}$ consistent with those market clearing conditions.

Lemma C.2 Given the parameters $\{\epsilon, \kappa, \tau, \alpha, \zeta^s_m, \nu^s_m, \varsigma^s_m\}$ and observables $\{\mathbf{N}_{Wm}, \mathbf{N}_{Rm}, \mathbf{q}, \mathbf{p}, \mathbf{t}\}$, there exists a unique set of vectors $\{\mathbf{X}^L, \mathbf{X}^H, \mathbf{X}_S\}$ such that conditions (C.6), (C.7), and (C.8) hold for all j.

Proof. The proof is identical to the proof of Lemma C.1.

Decomposition of wages and employment amenities. We have shown the uniqueness of composite employment amenities that incorporate wages (equation C.2). Given that we observe wages by education and industry for each model location, we can now decompose the amenities in the tradable sector $\hat{\mathbf{E}}^s_G$ into a non-wage component $\mathbf{E}^s_G$ and wages. We can also determine the college premium, w^H_{Sj}/w^L_{Sj}, but not wage levels, in the non-tradable sector.

Lemma C.3 Given the parameters $\{\epsilon, \kappa, \tau, \alpha, \zeta_m^s, \nu_m^s, \varsigma_m^s\}$ observables $\{\mathbf{N}_{Wm}, \mathbf{N}_{Rm}, \mathbf{q}, \mathbf{p}, \mathbf{t}, \widehat{\mathbf{w}}_G^s\}$, there exists a unique vector $\mathbf{E}_G^s$ for each $s \in \{L, H\}$ and a unique college wage premium in the non-tradable sector.

Proof. Note, by inspection of the indirect utility function (3.1) and choice probability (3.3), that uniqueness of $\{\hat{\mathbf{E}}^L, \hat{\mathbf{E}}^H, \hat{\mathbf{E}}_S\}$ and $\mathbf{X}_m^s$ implies that choice probabilities are also unique, conditional on observables. Here each element of $\mathbf{X}_m^s$ is $X_{mi}^s = X_i^s X_{mi}$ This means that there is a unique mapping between education-industry-specific wages in the tradable sector observed in the data, $\widehat{w}_{Gj}^s$, and their model counterpart, w_{Gj}^s, as given by equation (A.3). Once wages are known, we can solve for $E_j^s = \hat{E}_j^s / w_{Gj}^s$, where we used the fact that $\hat{E}_{Gj} = 1$.

Next, observe that in the non-tradable sector, $\hat{E}_j^s \hat{E}_{Sj} = E_j^s E_{Sj} w_{Sj}^H$. Though we cannot separately identify amenities from wages, we can determine the college wage premium as

$$\frac{w_{Sj}^H}{w_{Sj}^L} = \frac{\hat{E}_j^H \hat{E}_{Sj}}{\hat{E}_j^L \hat{E}_{Sj}} \frac{\hat{E}_j^L}{\hat{E}_j^H}, \tag{C.9}$$

since both ratios on the right-hand side are identified.

Existence and uniqueness of local productivities. The following result demonstrates that there are unique vectors of parameters that determine local productivity in tradable sector, non-tradable sector, and construction that are consistent with observed data and unobserved skill and occupation shares.

Lemma C.4 Given the parameters $\{\epsilon, \kappa, \tau, \alpha, \zeta_m^s, \nu_m^s, \varsigma_m^s\}$, observables $\{\mathbf{N}_{Wm}, \mathbf{N}_{Rm}, \mathbf{q}, \mathbf{p}, \mathbf{t}, \widehat{\mathbf{w}}_G^s\}$, employment amenities in the tradable sector $\mathbf{E}_G^s$, college wage premium in the non-tradable sector w_{Sj}^H / w_{Sj}^L, and residential amenities $\mathbf{X}_m^s$, there exist unique vectors $\omega_m \in \mathbb{R}_{++}^I$ and $\mathbf{A}_m \in \mathbb{R}_{++}^I$ for each $m \in \{G, S\}$, and a unique vector $\widetilde{\boldsymbol{\phi}} \in \mathbb{R}_{++}^I$.

Proof. There is sufficient information to construct a unique matrix of choice probabilities. Thus, the results follow immediately from equation (C.1), the zero-profit condition (3.21), and the land and floorspace market clearing conditions, (3.24) and (3.25).

Wages in the non-tradable sector. Note that our model is overidentified because employment amenities determine both local employment by industry and education and, as shown in equation (C.9), the college wage premium in the non-tradable sector. Thus, while our quantitative model takes wages in the tradable sector directly from the data, wages in the non-tradable sector are determined within the model. To identify wages in the non-tradable sector, we use the values of $\mathbf{A}_m$ and ω_m, and equation (3.15).

Existence and uniqueness of exogenous components of amenities and productivity. The last result demonstrates that there are unique vectors of parameters that determine local amenities that are consistent with observed data and unobserved skill and occupation shares.

Lemma C.5 Given the parameters $\{\epsilon, \kappa, \tau, \alpha, \zeta_m^s, \nu_m^s, \varsigma_m^s\}$, observables $\{\mathbf{N}_{Wm}, \mathbf{N}_{Rm}, \mathbf{q}, \mathbf{p}, \mathbf{t}, \widehat{\mathbf{w}}_G^s\}$, employment amenities in the tradable sector $\mathbf{E}_G^s$, college wage premium in the non-tradable sector w^H_{Sj}/w^L_{Sj}, residential amenities $\mathbf{X}^s_m$, and productivities $\mathbf{A}_m$ there exist unique vectors a_m and x^s_m.

Proof. The results follow immediately from equations that determine local productivity and amenities, (3.26) and (3.27).

D. Measuring Relocation of Residence

We define a measure of the magnitude of shifts in the distribution of residents between our benchmark and counterfactual economies, which we call the *relocation index*, as follows.

Consider all workers with skill s and occupation o who have chosen to work in industry m. Note that the choice of industry occurs before these workers know the values of their idiosyncratic location preference shocks. After these shocks are observed, the workers will choose the residence-workplace location pair. The measure of type-(s, o, m) workers who have chosen residential location i is $\pi^{so}_{mi} = \sum_j \pi^{so}_{mij}$. Next, assume that in the counterfactual each worker draws exactly the same vector of location preference shocks as in the benchmark economy but may draw a different industry preference shock. The measure of type-(s, o, m) workers who have chosen residential location i is $\tilde{\pi}^{so}_{mi} = \sum_j \tilde{\pi}^{so}_{mij}$, where $\tilde{\pi}$ are choice probabilities in the counterfactual economy.

The assumption that each worker experiences the same location preference shocks implies that, conditional on having chosen the same industry m, a worker will only choose to move to a different residential location i if the value of living in i, relative to all other locations, has fallen. The relative value of living i falls if and only if the probability of choosing this locations falls. Therefore, the magnitude of the relocation of type-(s, o, m) workers to/from location i is

$$\Delta\pi^{so}_{mi} = \tilde{\pi}^{so}_{mi} - \pi^{so}_{mi}.$$

Then, the economy-wide *relocation index* is equal to

$$\frac{1}{2}\sum_s \sum_o \sum_m \sum_i |\Delta\pi^{so}_{mi}|,$$

where we divided by 2 in order to adjust for the double-counting of movers.[55] We can also define the relocation index at the level of MSAs in the same way.

We calculate that the relocation index is 5% at the level of model locations and 3.3% at the level of MSAs. That is, about 2/3 of relocations between the benchmark and the counterfactual economies are relocations across metro areas and the remaining 1/3 are relocations within metro areas.

[55] When a worker relocates out of location i he also relocates into some other location i'.

E. Measuring Welfare Changes

Overall welfare. Our measure of worker's welfare is V^{so}, given by (3.7). As v^{so}_{mij} is proportional to optimal composite consumption, $\widetilde{w}^{so}_{mij} p_i^{-\beta} q_i^{-\gamma}$, the percentage change in consumption-equivalent welfare is equal to the percentage change in V^{so}. To find the economy-wide change in welfare, we compute the percentage change in the weighted-average of V^{so}, i.e., $V \equiv \sum_s \sum_o \mathrm{I}^{so} V^{so}$. In our calculations, we adjust the counterfactual disutility of commuting, d^{so}_{mij}, to reflect changes in commuting frequencies but not the changes in ς^s_m, the aversion to work from home.

Sources of welfare gains. We are interested in the relative roles of changes in consumption, commuting costs, and amenities. Thus, we compute changes in weighted-average indirect utilities and isolate each of these sources. To measure the part from *consumption only*, we compute

$$V^{so}_{\mathrm{C}} = \sum_m \sum_i \sum_j \pi^{so}_{mij} \widetilde{w}^{so}_{mij} p_i^{-\beta} q_i^{-\gamma}. \tag{E.1}$$

The part from *consumption and commuting costs* is computed as

$$V^{so}_{\mathrm{CC}} = \sum_m \sum_i \sum_j \pi^{so}_{mij} \left(1/d^{so}_{mij}\right) \widetilde{w}^{so}_{mij} p_i^{-\beta} q_i^{-\gamma}. \tag{E.2}$$

Finally, the contribution of *consumption, commuting costs, and amenities* to welfare is computed as

$$V^{so}_{\mathrm{CCA}} = \sum_m \sum_i \sum_j \pi^{so}_{mij} X^s_{mi} E^s_{mj} \left(1/(g_{ij} d^{so}_{mij})\right) \widetilde{w}^{so}_{mij} p_i^{-\beta} q_i^{-\gamma}. \tag{E.3}$$

The effect of amenities comes both from endogenous changes in residential amenities X^s_{mi} and migration to places with different amenities. As in the case of total welfare, we adjust d^{so}_{mij} to reflect changes in commuting frequencies but not in the telework aversion.

Landlord's income. We do not take a stance on the weight of landlords in the social welfare function and compare changes in their income alongside changes in workers' welfare. Landlords' only income source are proceeds from land sales, and their aggregate income is

$$\sum_i \eta_i q_i H_i. \tag{E.4}$$

F. In Focus: New York Metropolitan Area

In Section 5.2 of the main paper, we discussed how the reduction in the work-from-home aversion affects the largest metropolitan area in the country-New York. Here we provide a more in-depth discussion of spatial changes in the New York metro area.

Figure F.1 shows reallocation patterns for all residents and all jobs. Let us now take a look at the breakdown of movements of residents. As panel (a) makes clear, workers with telecommutable occupations overwhelmingly leave central areas and move to peripheral areas-the same pattern we see countrywide. In panel (b), we see workers with non- telecommutable occupations move downtown in signficiant numbers, off-setting much of the telecommutable exodus.

In panel (c), we see a heavy exodus of tradable industry jobs from nearly all locations near the center of the city. At the same time, panel (d) shows strong tradable industry job gains for downtown, with some losses in peripheral suburbs.

Panel (e) maps changes in floorspace prices, which are most strongly negative in downtown Manhattan, and positive in many outlying areas. Panel (f) maps changes in the price of non-tradables. In outlying areas they mostly increase, which can be interpreted as indicating that rising demand from more residents overwhelms the cost-lowering effect of lower floorspace prices. In some of the most central locations the price of non-tradables falls, indicating that the effect of lower floorspace prices dominates.

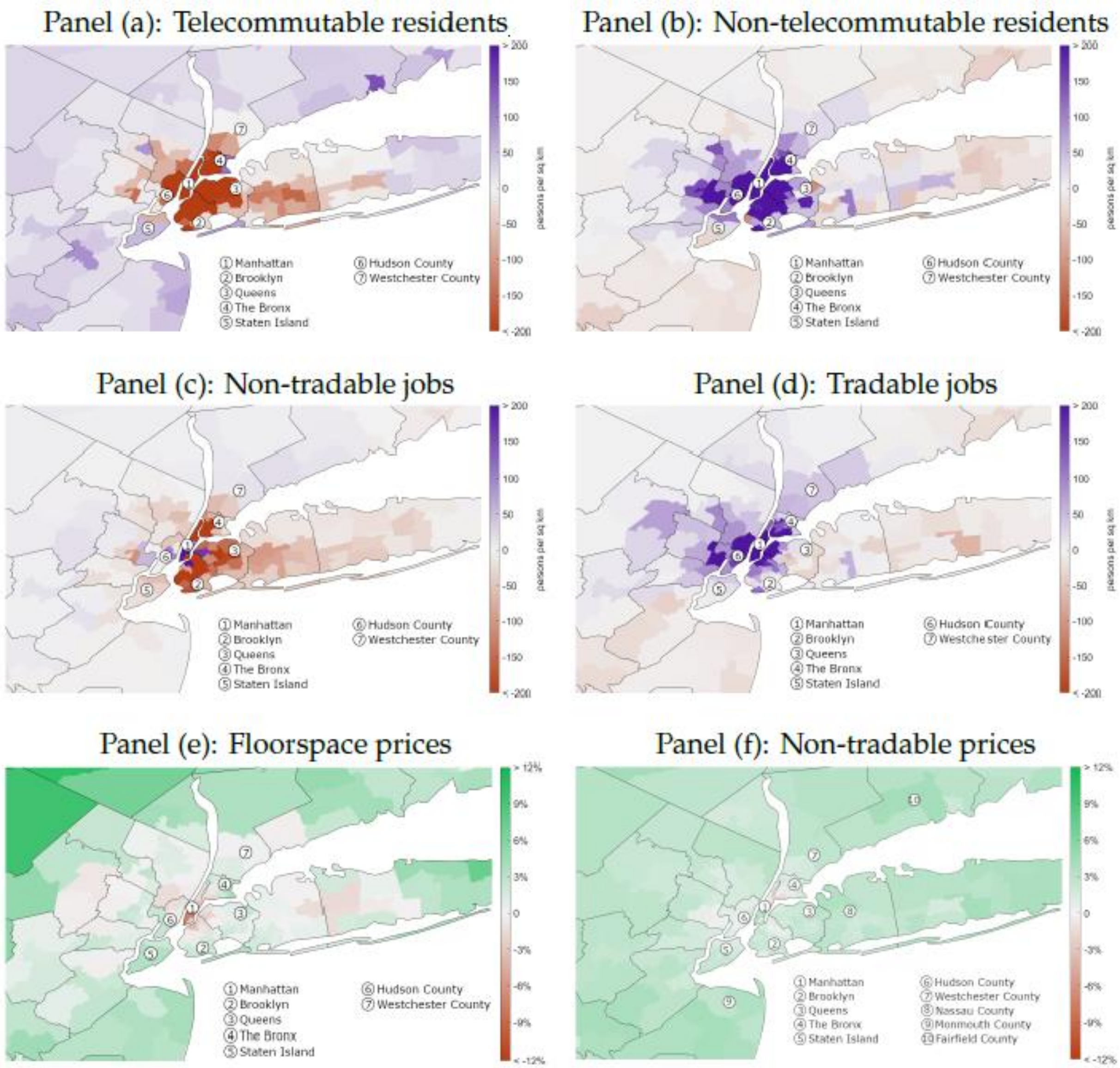

Figure F.1. New York metro area, predicted changes in residence, jobs, and prices

Note: The maps show absolute changes in the number of telecommutable residents (panel a), non-telecommutable residents (panel b), non-tradable jobs (panel c) and tradable jobs (panel d) per square kilometer in the main counterfactual exercise. Panel (e) shows percentage changes in floorspace prices and panel (f) shows percentage changes in non-tradable goods prices.

G. Further Discussion of Alternative Counterfactuals

In this section, we study alternative counterfactuals in order to understand which channels are important in driving resident and job reallocations, as well as aggregate changes. We start with a world in which the aversion to telecommuting decreases but workers are unable to move and floorspace supply does not change (counterfactual 1). Then we switch on the reallocation of workers to new residences and jobs (counterfactual 2). After that, floorspace supply adjusts (counterfactual 3). Next, residential amenities adjust (counterfactual 4), and then local productivity adjusts (counterfactual 5). This last stage brings us all the way up to our original focus point-the long run with full adjustment. Finally, we run a counterfactual in which working at home contributes to productive externalities in the main job site as much as working on site by setting *ty = 1* (counterfactual 6).

Table G.1 reports results for each scenario. In counterfactual (1), we see that average welfare rises as soon as remote work becomes more accessible, even before workers can move and floorspace supply can change. However, gains are only experienced by telecommutable workers. These enjoy higher income from a more productive combination of at-home and on-site time, and less time spent commuting. Among those who cannot work from home, non-college workers see essentially no change while college workers have 1.7% lower welfare. This can be attributed to the impact of general equilibrium labor supply changes on income for each group. A larger proportion of college workers are remote-capable, and they are slightly more productive working at home. In the counterfactual this leads to an aggregate increase in the supply of college-educated labor. This bolsters the wages of non-college workers, their complements; and puts downward pressure on the wages of non-telecommutable college workers, who compete directly.

In counterfactual (2), when workers are allowed to choose new jobs and residences but floorspace allocations remain the same, non-telecommutable workers are able to increase their income by moving into jobs in central locations left behind by remote workers. Non-telecommutable workers also take advantage of reduced floorspace demand in central areas to move slightly closer to their jobs, reducing their time spent commuting by 0.6%. We also see a gap emerge between the income gains of college remote-capable workers, and the gains of their non-college counterparts. This can be attributed to an industry composition effect: a greater proportion of college workers are employed in the tradable sector, and are thus able to take advantage of easier remote work to match with more productive job sites. Non-tradable employment, however, follows residents to less productive locations, as evidenced by the increase in non-tradable prices. This reduces income gains for non-college remote workers. This counterfactual also leads to the most extreme shifts in floorspace prices of any of the scenarios we consider-under-utilized, centrally located commercial floorspace faces deep price cuts, while surging demand for residential floorspace drives steep price increases.[55]

Table G.1. Aggregate results, alternative counterfactuals

WFH aversion falls:	✓	✓	✓	✓	✓	✓
Residents and jobs reallocate:	—	✓	✓	✓	✓	✓
Floorspace adjusts:	—	—	✓	✓	✓	✓
Residential amenities adjust:	—	—	—	✓	✓	✓
Labor productivity adjusts:	—	—	—	—	✓	✓
Telecommuters add to productivity:	—	—	—	—	—	✓
	(1)	(2)	(3)	(4)	(5)	(6)
Income, % chg						
All workers	2.9	5.7	3.6	3.6	1.6	3.6
Non-college, non-telecommutable	0.5	6.3	2.5	2.6	0.6	2.7

Non-college, telecommutable	7.5	2.2	3.9	3.9	1.8	4.0
College, non-telecommutable	-1.1	4.5	0.2	0.2	-1.7	0.1
College, telecommutable	6.7	7.7	7.4	7.3	5.3	7.2
Floorspace prices, % chg						
Residential	1.6	16.0	1.1	0.4	-0.8	-0.1
Commercial	-5.2	-16.5	—	—	—	—
Non-tradable goods prices, % chg	0.4	2.7	3.5	3.4	3.5	3.3
Average time to work, % chg	0.0	46.4	51.5	52.2	52.0	52.9
Time spent commuting, all workers, % chg	-17.4	-19.3	-20.6	-20.4	-20.5	-20.2
Time spent commuting, commuters (θ=1), % chg	0.0	-0.6	-0.7	-0.3	-0.4	0.0
Distance traveled, all workers, % chg	-17.5	-19.9	-21.4	-20.9	-21.1	-20.5
Average WFH days/week, chg	0.7	0.9	0.9	0.9	0.9	0.9
Welfare, % chg						
All workers, % chg	7.6	7.5	8.9	9.1	7.2	9.2
Non-college, non-telecommutable	0.0	0.8	0.1	0.2	-1.5	0.3
Non-college, telecommutable	48.9	39.9	49.1	49.6	46.9	50.1
College, non-telecommutable	-1.7	-0.5	-1.6	-1.8	-3.4	-1.8
College, telecommutable	21.3	22.7	30.0	30.3	28.0	30.5
Landlord income, % chg	2.1	25.5	3.1	2.9	1.0	2.7
Due to change in demand	2.2	28.1	3.9	3.9	1.9	3.9
Due to reallocation to low η_i	0.0	-2.6	-0.7	-1.0	-0.8	-1.2

Note: Columns (1)-(6) present results from counterfactuals with different margins of adjustment turned on, as specified in the header of the table. Welfare changes in columns (2)-(6) are measured as changes in expected utility (equation 3.7). Since in the first counterfactual workers cannot move, welfare changes in column (1) are measured as changes in the utility from consumption and commuting.

In counterfactual (3), allowing floorspace supply to adjust sharply cuts income gains by non-telecommutable workers, as center-city offices are downsized and more employment shifts to less central locations. This also brings double-digit shifts in floorspace prices and land income down to a 1.1% and a 3.1% increase, respectively. The main impact of allowing residential amenities adjust in counterfactual (4) is to cause non-telecommutable workers to choose residences that are slightly farther away from their jobs, as some of the amenities have now followed remote workers out to the suburbs. In counterfactual (5), our main counterfactual, we see the impact of reduced agglomeration externalities from having workers out of the office. Income gains are cut by 2 percentage points across the board, in each category of worker.

In counterfactual (6) working at home contributes to productive externalities in the main job site as much as working on site ($\psi = 1$). This could happen if remote interaction technology advances to the point that it can fully simulate the experience of being co-located with one's collaborators thus eliminating any disadvantage remote work has in sparking spontaneous spillovers.5[6] Comparing columns 6 and 4 of Table G.1, we can see that income losses from reduced productivity are neatly reversed under this alternative assumption.

The top three panels in Figure G.1 plot reallocations of residents across counterfactuals (2) through (6). Obviously, in the first counterfactual, there is no reallocation of residents. Panel (a) shows the overall reallocation. Here, we see that each step accentuates the initial pattern-a net movement of residents from denser to less dense locations. Panels (b) and (c) break this down by occupation type, and reveal a heterogeneous pattern. For workers who can work from home in panel (c), things look similar to the overall average-each successive step accentuates reallocation from center to periphery. For workers who cannot work from home, in panel (b), the opposite happens-the reallocation from periphery to center is strongest in the second and third counterfactuals. In the fourth and fifth counterfactuals the reallocation into the city is smaller, as the telecommuting workers end up carrying a part of the city's amenities out with them. Finally, in the sixth counterfactual, increased productivity in the periphery draws additional non-telecommutable workers out. In this scenario, non-telecommutable workers move out of medium-density locations, into both peripheral and central locations.

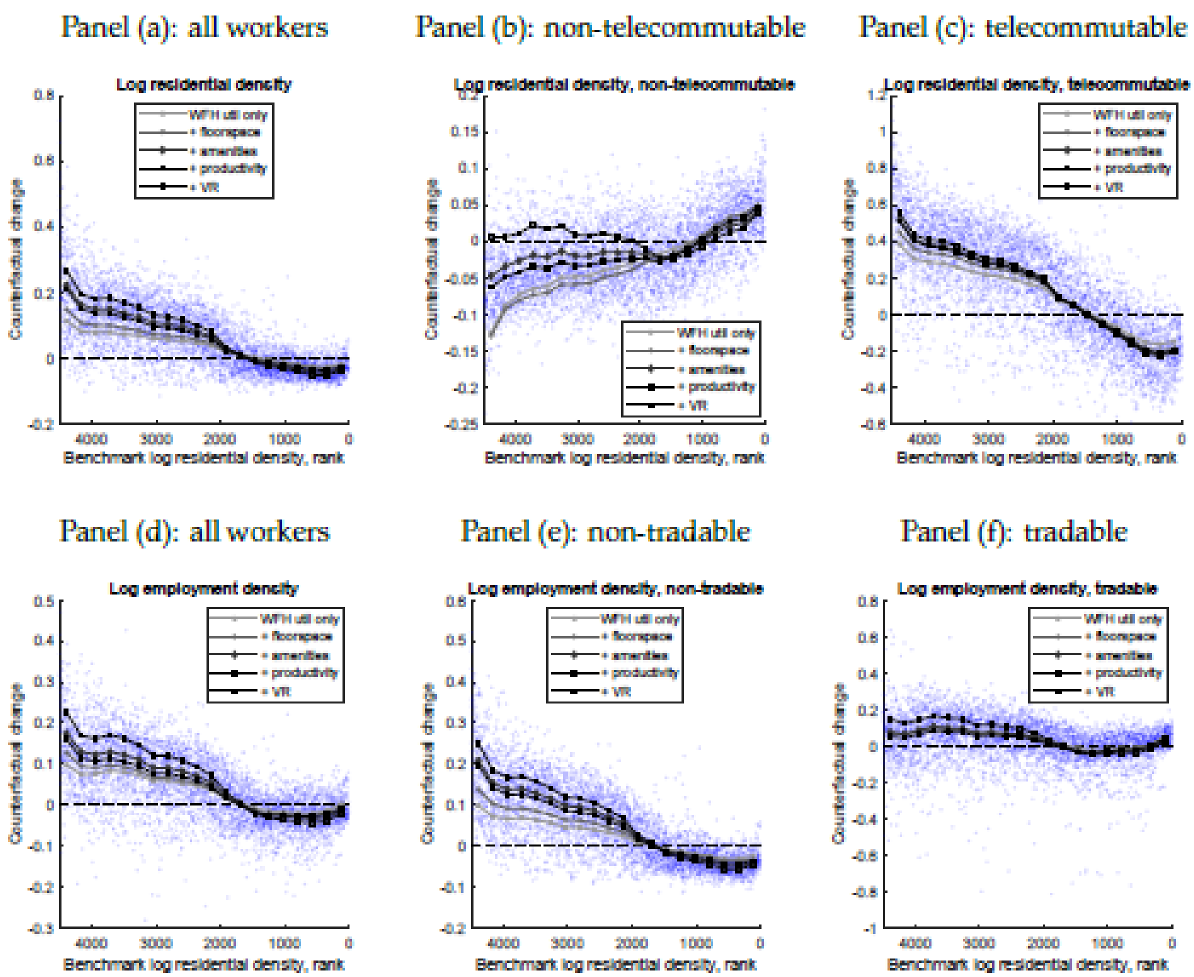

Figure G.1. Changes in residents and jobs, counterfactuals (2)-(6)

Note: This figure shows the relationship between residential density rank of model locations and counterfactual change in the resident density (panels a, b, and c) and job density (panel d, e, and f). Panel a shows changes for all residents, panel b shows changes for non-telecommutable residents, and panel c shows changes for telecommutable residents. Panel d shows changes for all jobs, panel e shows changes for non-tradable jobs, and panel f shows changes for tradable jobs. The scatterplot in blue shows individual datapoints, and black and grey markers plot averages by ventile: i.e., below the 5th percentile, from the 5th to the 10th, and so on.

The bottom three panels in Figure G.1 show reallocations of jobs across the second through sixth counterfactuals. As with residents, each successive step accentuates the main pattern of reallocation towards less dense locations. Glancing at panel (e), it is clear this is mostly driven by non-tradable sector jobs following the movement of residents. Looking at panel (f), it is interesting to note that the variations between counterfactuals (2), (3), (4), and (5) have very little effect on the reallocation of tradable jobs. Reallocations of labor in the tradable sector are driven by the broadening of the labor market which is already fully operative by counterfactual (2). In counterfactual (6), however, less-dense locations see a significant jump in competitiveness, as remote workers begin contributing to local TFP.

H. Counterfactual: Increased Productivity of Remote Work

In this section we consider a counterfactual in which increased working from home is due solely to increased productivity, rather than solely to changes in preferences as in the baseline counterfactual. While many of the patterns are similar to those seen in the baseline, it produces unrealistic increases in the wages of telecommuters, and performs poorly in predicting where people have actually moved since February 2020. Table H.1 reports the changes in productivity of work from home required to attain the predicted increase in work from home frequency. The productivity of remote work must go up by 69-195% depending on the type of worker.

Distributions of residents and jobs. Figure H.1 shows changes in residents. Comparing it with Figure 7, we can see that the overall patterns are similar, except that the pattern of decentralization of residents among the densest locations and largest metro areas is more mixed. Next, comparing Figure H.2 with Figure 8, we can see that as with residents, the overall patterns of job reallocation are similar between this and the baseline counter- factual. The main driving force for the shifts in residents and jobs is greater attractiveness of work from home, whether due to lower aversion to it or due to its higher productivity.

Table H.1. Relative productivity of remote work, baseline vs. counterfactual

Description	Variable	Benchmark	Counterfactual	% Change
Non-college, non-tradable	ν_S^L	0.9734	2.8520	192.99%
Non-college, tradable	ν_G^L	1.1351	3.3519	69.48%
College, non-tradable	ν_S^H	1.0114	1.7141	195.29%
College, tradable	ν_G^H	1.2054	2.1614	79.31%

Note: The table shows calibrated values of the relative productivity of remote work.

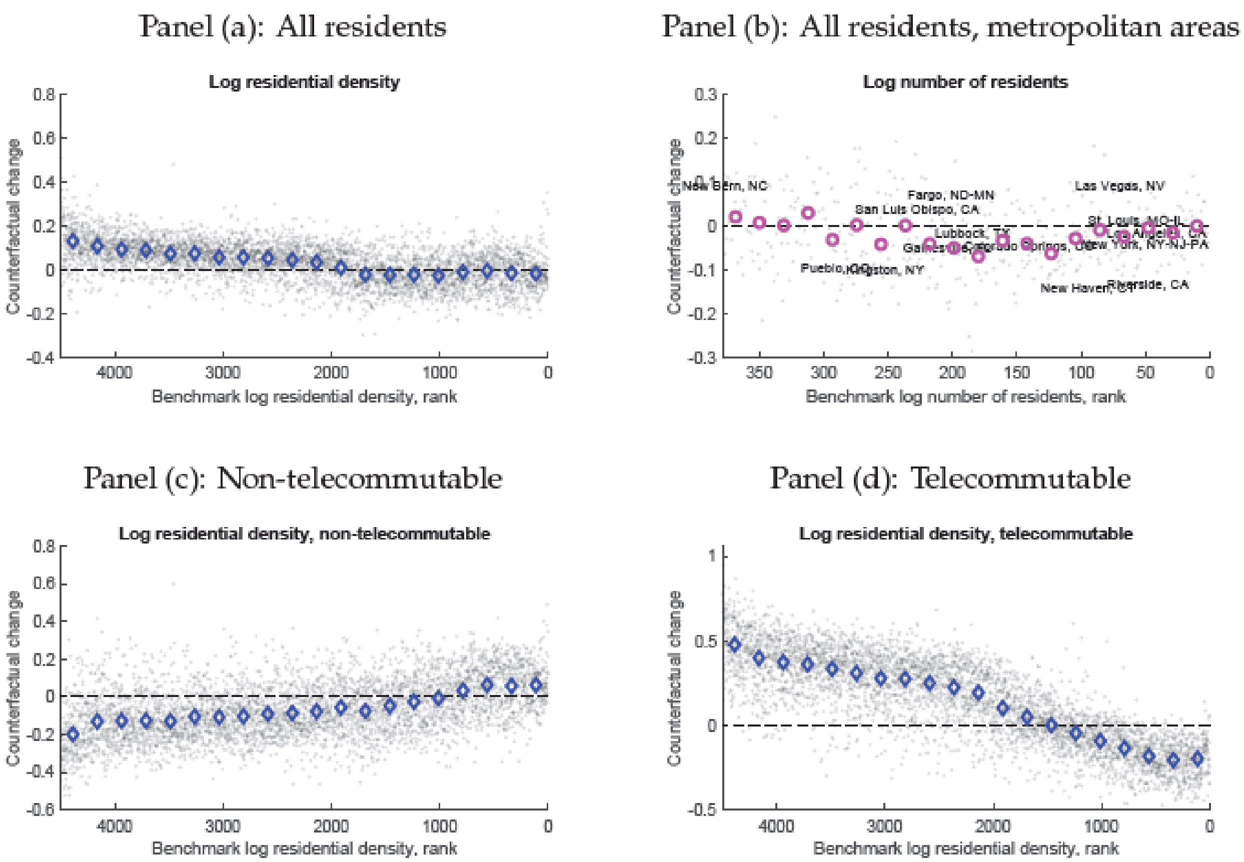

Figure H.1. Changes in Residents

Note: Panel (a) shows the relationship between residential density rank for model locations and counterfactual change in log residential density. Panel (b) shows the relationship between total resident rank for metro areas and the counterfactual change in log total residents. Panel (c) repeats the exercise for non-telecommutable residents by model location, while panel (d) does the same for telecommutable residents. Scatterplots in gray show individual model locations or MSAs, while diamonds or circles represent averages by ventile: i.e., below the 5th percentile, from the 5th to the 10th, etc.

Aggregate results and welfare effects. Table H.2 reports aggregate results from this counterfactual. Comparing with Table 7, we can see that changes in aggregate commuting behavior are similar. This is not surprising, as the same changes in average telecommuting frequencies are targeted in the calibration. However, the predictions for changes in income are very different. An average worker earns 50% more, with the increase driven entirely by telecommutable workers. Among these, college workers earn 69% more, while noncollege workers earn over 219% more. We find it hard to call the prediction of such increases in the wages of telecommutable professions, due solely to technological changes in the year or so after March 2020, anything but very unrealistic.

Evidence during Covid-19. Finally, we compare this counterfactual's predictions about reallocations of residents and changes in floorspace prices with observed migration and changes in housing rents and prices between 2019 and 2021, as we did in Section 5.4.

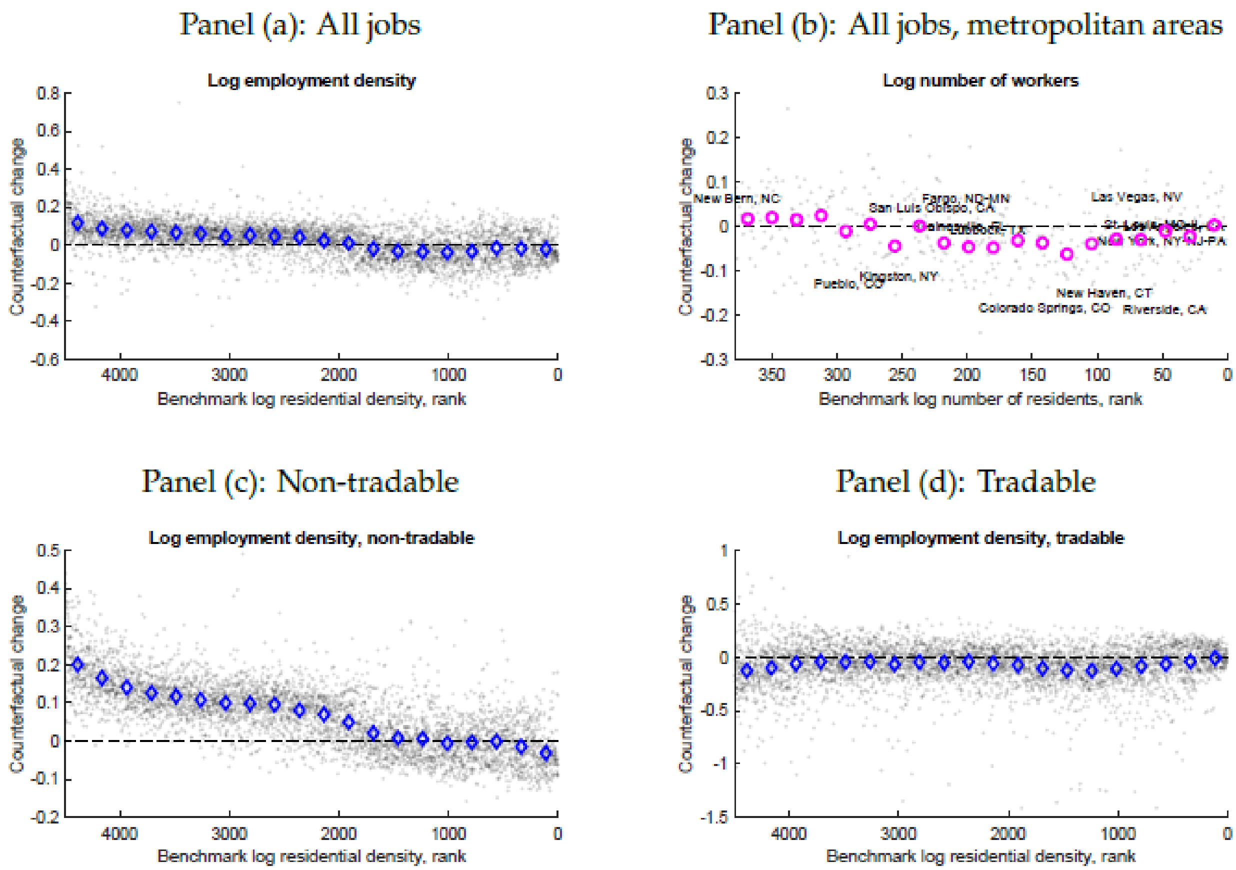

Figure H.2. Changes in Employment

Note: Panel (a) shows the relationship between residential density rank for model locations and counterfactual change in log job density. Panel (b) shows the relationship between total resident rank for metro areas and the counterfactual change in log total jobs. Panel (c) repeats the exercise for non-tradable jobs by model location, while panel (d) does the same for tradable jobs. Scatterplots in gray show individual model locations or MSAs, while diamonds or circles represent averages by ventile: i.e., below the 5th percentile, from the 5th to the 10th, etc.

Comparing column (1) in Table H.3 with column (1) in Table 8, we see that when it is assumed that increased work from home is driven only by productivity, the model is a much poorer predictor of observed shifts in residential population: the R^2 falls from 0.29 to 0.1. Once initial density is controlled for (columns 2, 4, and 6), in fact, model projections have negative or zero correlation with actual changes. This is in contrast to the baseline counterfactual, which is a significant predictor of actual changes, even after density controls. Comparing the results for real estate prices in Table H.4 with those in Table 9, we see that assuming that the increase in remote work is due to productivity changes does not improve the predictive power of the model.

One of the reasons for the inability of this counterfactual to predict observed shifts in population becomes clear when comparing Figures H.1 and 7: non-telecommutable workers move more strongly away from the periphery to central locations, dampening the net pattern of core-periphery reallocation. This is also a consequence of gigantic remote worker wage increases-they use their higher incomes to rent more floorspace, pricing non-remote workers out of the rural and suburban real estate markets.

Table H.2. Aggregate results

		Non-college			College		
	All workers	All	Non-tel.	Tel.	All	Non-tel.	Tel.
Income, % chg	50.7	54.1	-3.5	219.0	44.7	2.1	68.8
Average time to work, % chg	57.6	53.5	-1.8	163.8	66.3	-1.9	94.2
Time spent commuting, % chg	-20.5	-18.8	-1.8	-84.7	-25.0	-1.9	-43.1
Average WFH days/week, chg	0.9	0.8	—	3.5	1.2	—	2.9
Floorspace prices, % chg	31.2	32.0	33.3	27.5	29.4	31.5	28.0
Non-tradable prices, % chg	10.8	10.9	10.9	11.0	10.4	10.4	10.4
Welfare, % chg							
Consumption only	32.2	34.8	-16.3	179.7	27.3	-10.9	48.7
+ commuting	29.8	33.8	-15.7	180.9	22.2	-10.2	41.3
+ amenities	29.1	33.6	-12.2	170.0	22.1	-5.0	38.2
Total welfare	30.1	21.9	-15.1	310.6	64.2	-9.3	87.5

Note: The table shows results of the counterfactual exercise in which the rise of telecommuting is driven by an increase in the productivity of work from home, as described in the text. “tel.” refers to telecommutable workers, and “non-tel.” to non-telecommutable workers. Price changes refer to the change in the average price faced by a member of the indicated group of workers.

Table H.3. Change in population during Covid-19, model vs. data

	(1)	(2)	(3)	(4)	(5)	(6)
Log chg residents, model	0.923	-0.166	0.512	-0.0579	0.552	-0.124
	(0.0404)	(0.0340)	(0.0437)	(0.0422)	(0.0737)	(0.0691)
Log density, data		-0.0786		-0.0633		-0.0547
		(0.00124)		(0.00191)		(0.00281)
Level of obs.	ML	ML	ML	ML	CZ	CZ
CZ fixed effects	No	No	Yes	Yes	—	—
Observations	4502	4502	4453	4453	723	723
R-squared	0.104	0.527	0.650	0.729	0.0723	0.391

Note: The table shows estimates from the regressions of log change in between December 2019 and December 2021 from Safegraph data on the log change in residents in the model and log residential density in 2012-2016. Standard errors are in parentheses. The regressions are estimated at the level of model locations (“ML”), with or without commuting zone fixed effects, or at the level of commuting zones (“CZ”). Regressions at the model location level with commuting zone fixed effects have fewer observations because some commuting zones correspond to model locations.

Table H.4. Changes in housing rents and prices during Covid-19, model vs. data

Panel (a): rents

	(1)	(2)	(3)	(4)	(5)	(6)
Log chg rents, model	0.413	0.189	0.421	0.541	0.711	2.841
	(0.152)	(0.170)	(0.185)	(0.210)	(1.621)	(2.197)
Log density, data		-0.0152		0.00779		0.130
		(0.00520)		(0.00656)		(0.0912)
Level of obs.	ML	ML	ML	ML	CZ	CZ
CZ fixed effects	No	No	Yes	Yes	—	—
Observations	1136	1136	1122	1122	98	98
R-squared	0.00646	0.0139	0.153	0.154	0.00200	0.0230

Panel (b): Prices

	(1)	(2)	(3)	(4)	(5)	(6)
Log chg prices, model	0.143	0.0990	0.332	0.415	-0.152	0.0300
	(0.0570)	(0.0895)	(0.0934)	(0.129)	(0.219)	(0.320)
Log density, data		-0.00193		0.00422		0.00903
		(0.00304)		(0.00453)		(0.0116)
Level of obs.	ML	ML	ML	ML	CZ	CZ
CZ fixed effects	No	No	Yes	Yes	—	—
Observations	4182	4182	4121	4121	688	688
R-squared	0.00150	0.00160	0.342	0.342	0.000705	0.00159

Note: The table shows estimates from the regressions of log change in rents (panel a) and prices (panel b) between December 2019 and December 2021 from Zillow on the log change in floorspace prices in the model and log residential density in 2012-2016. Standard errors are in parentheses. The regressions are estimated at the level of model locations ("ML"), with or without commuting zone fixed effects, or at the level of commuting zones ("CZ"). Regressions at the model location level with CZ fixed effects have fewer observations because some commuting zones correspond to model locations.

I. Robustness

I.1. No Penalty for Living Far from Home

One of the innovations of our framework is the penalty for living far from the job site that applies regardless of the frequency of commuting, g_{ij}. How different would our results be if we excluded g_{ij} from the location choice problem?

To answer this question, we recalibrate our model by imposing $z = 0$ which implies that $g_{ij} = 1$ for all location pairs. Without the penalty, those workers who commute very infrequently are almost completely untethered from their job sites and can live virtually anywhere, contrary to the evidence on the locations of telecommuters that constitutes *stylized fact #4* in Section 2. Column 2 of Table I.1 shows that all changes that we observed in our main counterfactual exercise (column 1) are greatly amplified: telecommutable workers relocate farther from job sites and their welfare gains are much more pronounced.

I.2. Equal Reduction in Work-from-Home Aversion

In our main counterfactual, we found that non-college workers experience somewhat larger reductions in their aversion to remote work. This gives boost to counterfactual welfare gains experienced by non-college workers, even though their welfare still increases by only 4%, compared to 20.5% for college workers, primarily because there are more workers who can work from home among college graduates than among their non-college counterparts (see Table 7). How sensitive are our results to the differences in calibrated changes in dislike for telework?

We recalibrate the post-Covid economy so that the aggregate reduction in work-from- home aversion is the same for all workers in all industries by targeting the overall, not education-industry specific, increase in work from home. The calibrated fall in the aversion parameter, ς_m^S is 49% for all types of workers. Column 3 of Table I.1 compares the results of this counterfactual to the main counterfactual (column 1). The welfare gains of telecommutable college graduates become larger and the losses of non-telecommutable college graduates become smaller. At the same time, for non-college graduates the gains turn smaller and the losses larger. This implies that the gap in welfare gains between college and non-college workers would be even greater if we assumed the same reduction in work from home aversion for all worker types.

I.3. Equal Floorspace Supply Elasticities

In our quantitative model, we use estimates of floorspace supply elasticities from Baum- Snow and Han (2021). To our knowledge, these are the only estimates at a sufficiently high level of resolution (Census tracts) that can be applied to our model locations (see the map of elasticities in Figure J.5). At the same time, these elasticities are significantly lower than those estimated in prior literature (see discussion in Section 4.2.1).

Table I.1. Aggregate results, robustness counterfactuals

	(1) Main CF	(2) τ=0	(3) Same chg ς_m^S	(4) Same η_i	(5) v_m^S=1
Income, % chg					
All workers	1.6	1.1	2.0	1.5	-0.7
Non-college, non-telecommutable	0.6	0.8	0.4	0.7	-0.5
Non-college, telecommutable	1.8	1.5	4.9	1.8	-2.6
College, non-telecommutable	-1.7	-0.2	-1.4	-2.0	-1.9
College, telecommutable	5.3	2.2	5.2	4.9	1.1
Floorspace prices, % chg					
Residential	-0.8	-1.7	-0.8	-1.6	-2.4
Commercial	0.0	0.0	0.0	0.0	0.0
Non-tradable goods prices, % chg	3.5	3.6	3.5	3.1	1.9
Average time to work, % chg	52.0	193.2	51.2	53.3	52.5
Time spent commuting, all workers, % chg	-20.5	-19.9	-20.5	-20.2	-20.6
Time spent commuting, commuters (θ=1), % chg	-0.4	-0.2	-0.3	0.1	-0.4
Distance traveled, all workers, % chg	-21.1	-21.1	-20.8	-20.0	-21.2
Average WFH days/week, chg	0.9	0.9	0.9	0.9	0.9
Welfare, % chg					
All workers, % chg	7.2	30.1	7.7	7.3	6.7
Non-college, non-telecommutable	-1.5	-1.5	-1.9	-1.5	-1.2
Non-college, telecommutable	46.9	110.6	40.6	47.8	44.9
College, non-telecommutable	-3.4	-2.3	-3.0	-3.8	-2.3
College, telecommutable	28.0	63.0	37.2	28.2	24.7
Landlord income, % chg	1.0	0.1	1.4	1.8	-1.3
Due to change in demand	1.9	1.4	2.3	1.8	-0.5
Due to reallocation to low η_i	-0.8	-1.3	-0.9	0.0	-0.8

Note: The table reports results of several alternative counterfactuals, as described in the text.

To evaluate the sensitivity of our results to these elasticities, we re-calibrate the model by assigning the elasticity of 1.75 (this corresponds to $\eta_i = 0.36$), as estimated in Saiz (2010), to all model locations. Column 4 of Table I.1 compares the results of this counterfactual to the main counterfactual (column 1). All results are quite close to the main counterfactual, which suggests that our predictions are robust to our choice of housing supply elasticities.

I.4. Equal Productivity of Remote Work

Our counterfactual results depend, to some extent, on the calibrated values of the relative productivity of remote work. In particular, many workers can increase their income by working from home more often because for most of the worker types remote work is more productive (see Table 5). To understand the role of exogenous productivity differences between on-site and remote work effort, we fix $v_m = 1$ for all types, recalibrate the model, and rerun the main counterfactual. The results in column 5 of Table I.1 show that, if remote work was as productive as on-site work, most workers would experience income losses and welfare gains would be less pronounced.

J. Additional Figures, Tables, and Maps

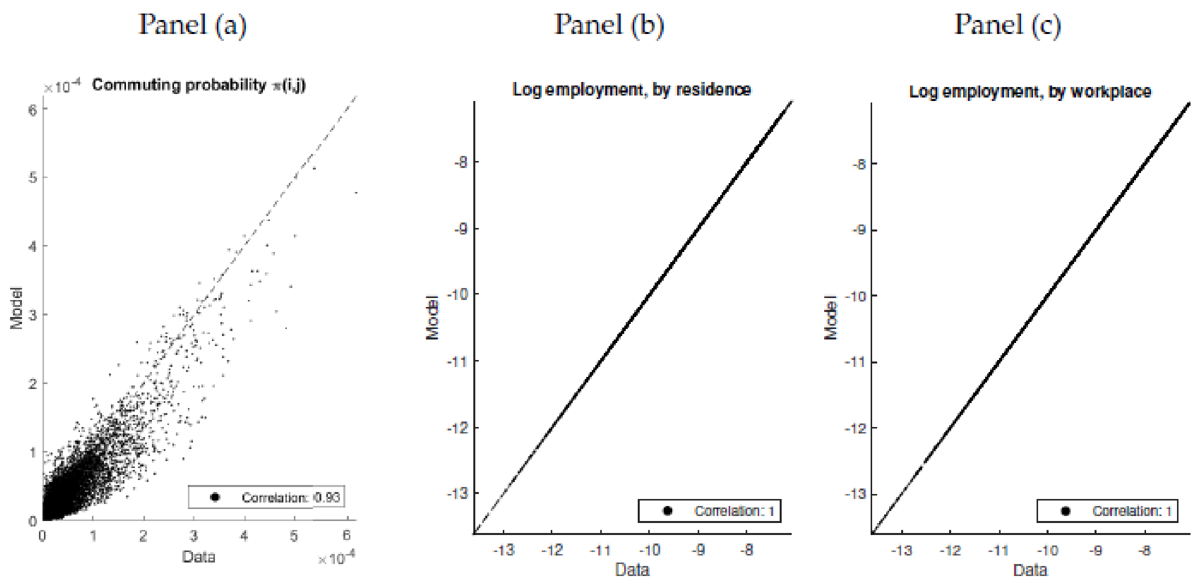

Figure J.1. Commuting flows and employment, model vs. data

Note: These scatterplots show the relationship between commuting flows (panel a), log residents (panel b), and log jobs (panel c) in the LODES data and their counterparts in the model. The dashed line is the 45-degree line. Since over 98% of location pairs in the data have zero commuters, the logarithmic version of panel (a) is not feasible.

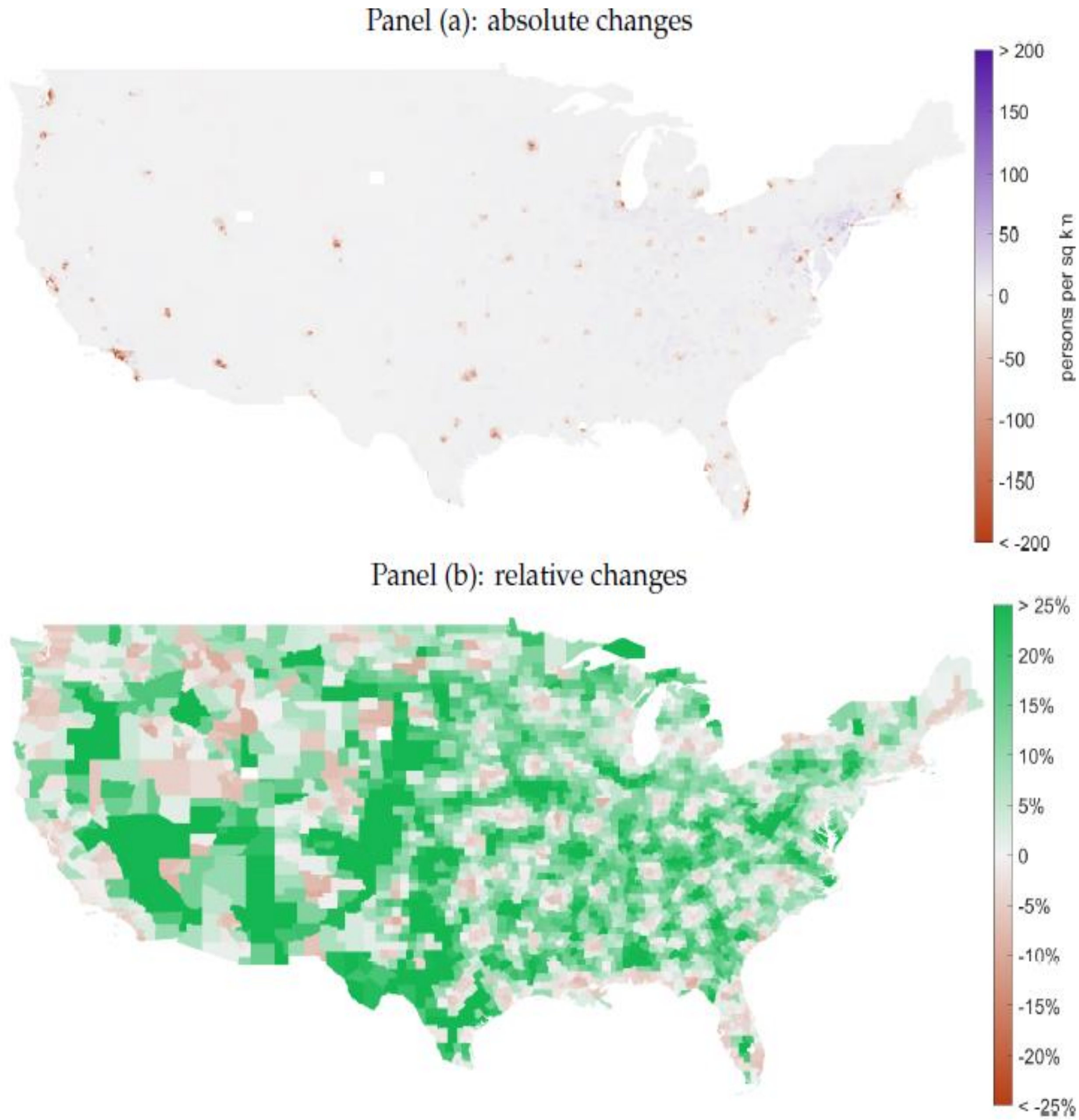

Figure J.2. Density of Residents

Note: Panel (a) shows absolute changes in the number of residents per square kilometer in each model location in the main counterfactual where the aversion for work from home falls and all endogenous variables adjust. Panel (b) shows percentage changes.

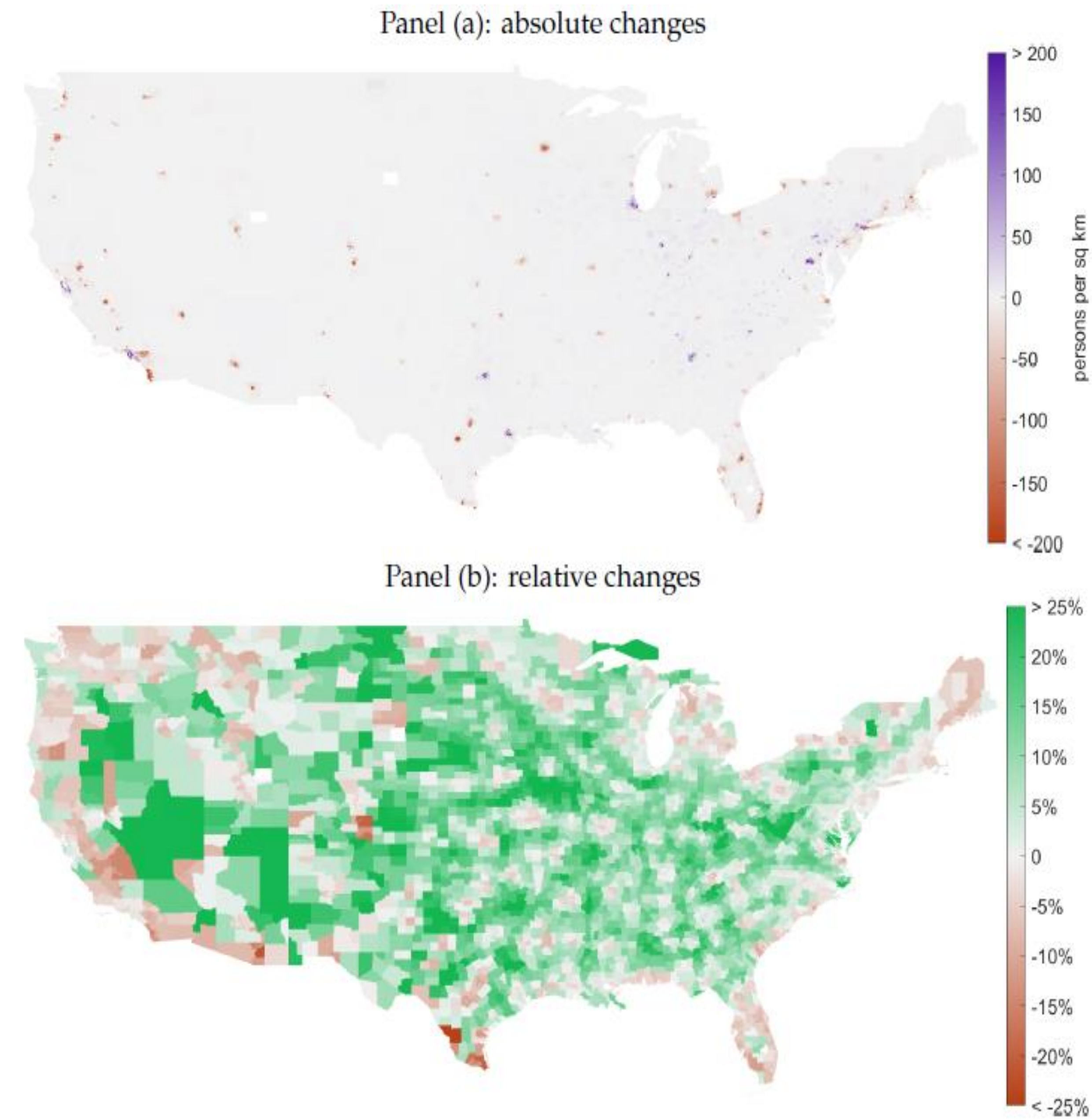

Figure J.3. Density of jobs

Note: Panel (a) shows absolute changes in the number of jobs per square kilometer in each model location in the main counterfactual where the aversion for work from home falls and all endogenous variables adjust. Panel (b) shows percentage changes.

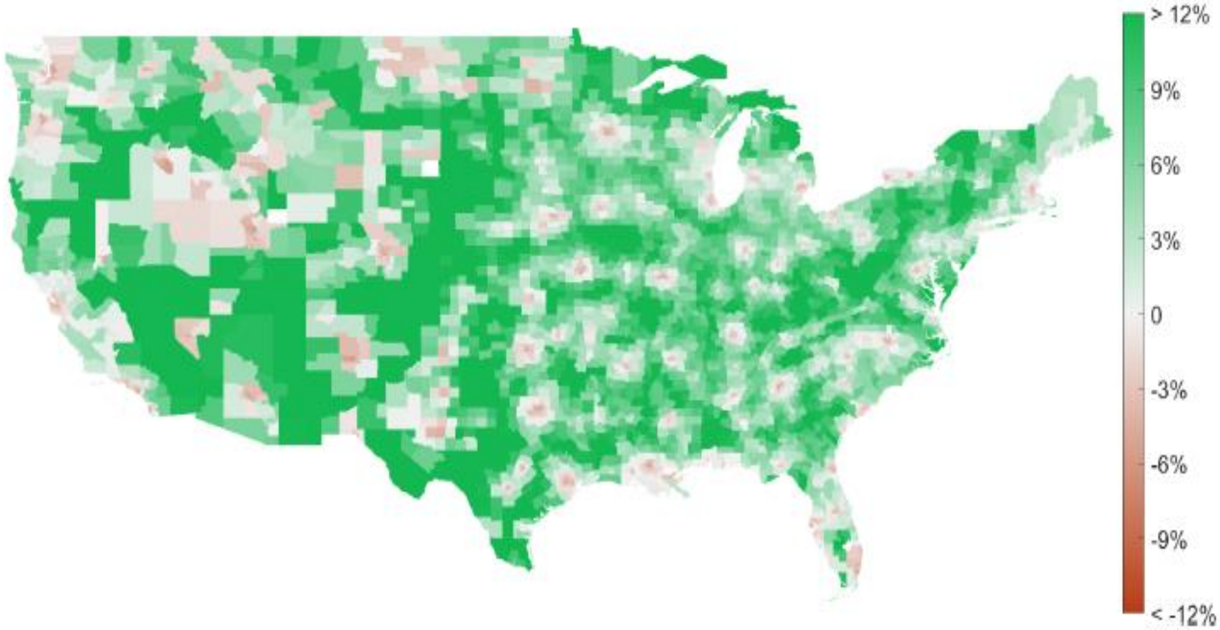

Figure J.4. Floorspace prices, percentage changes

Note: The map shows percentage changes in the price of floorspace in the main counterfactual where the aversion for work from home falls and all endogenous variables adjust.

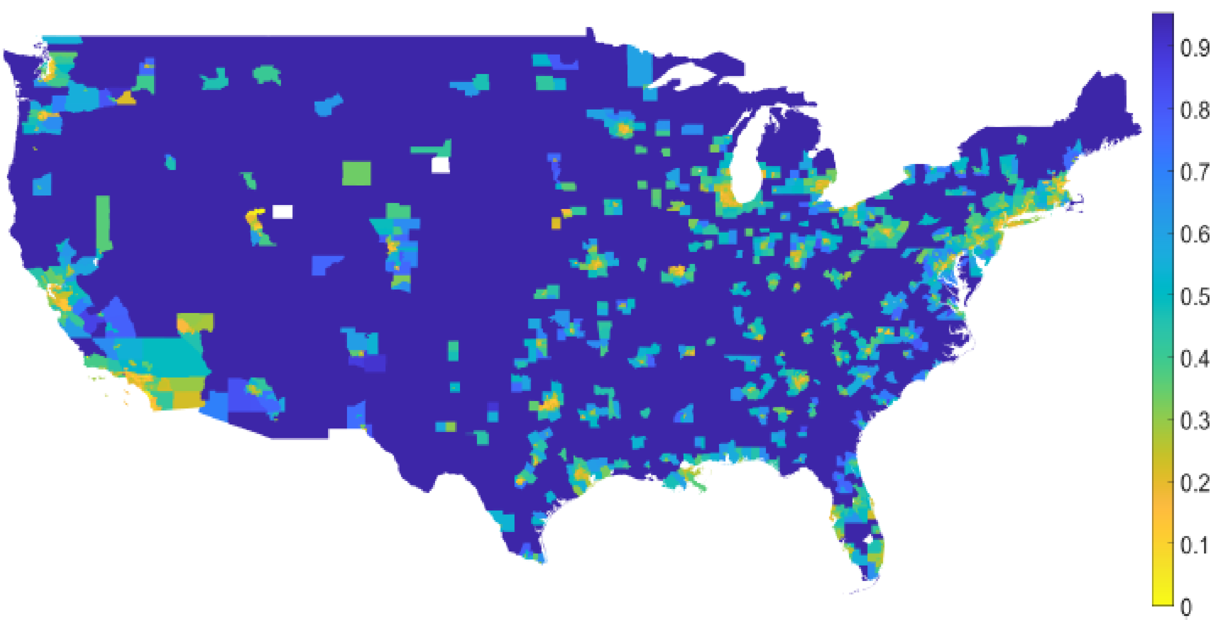

Figure J.5. Elasticities of floorspace supply

Note: This map shows the floorspace supply elasticities from Baum-Snow and Han (2021), aggregated to the level of our model locations.

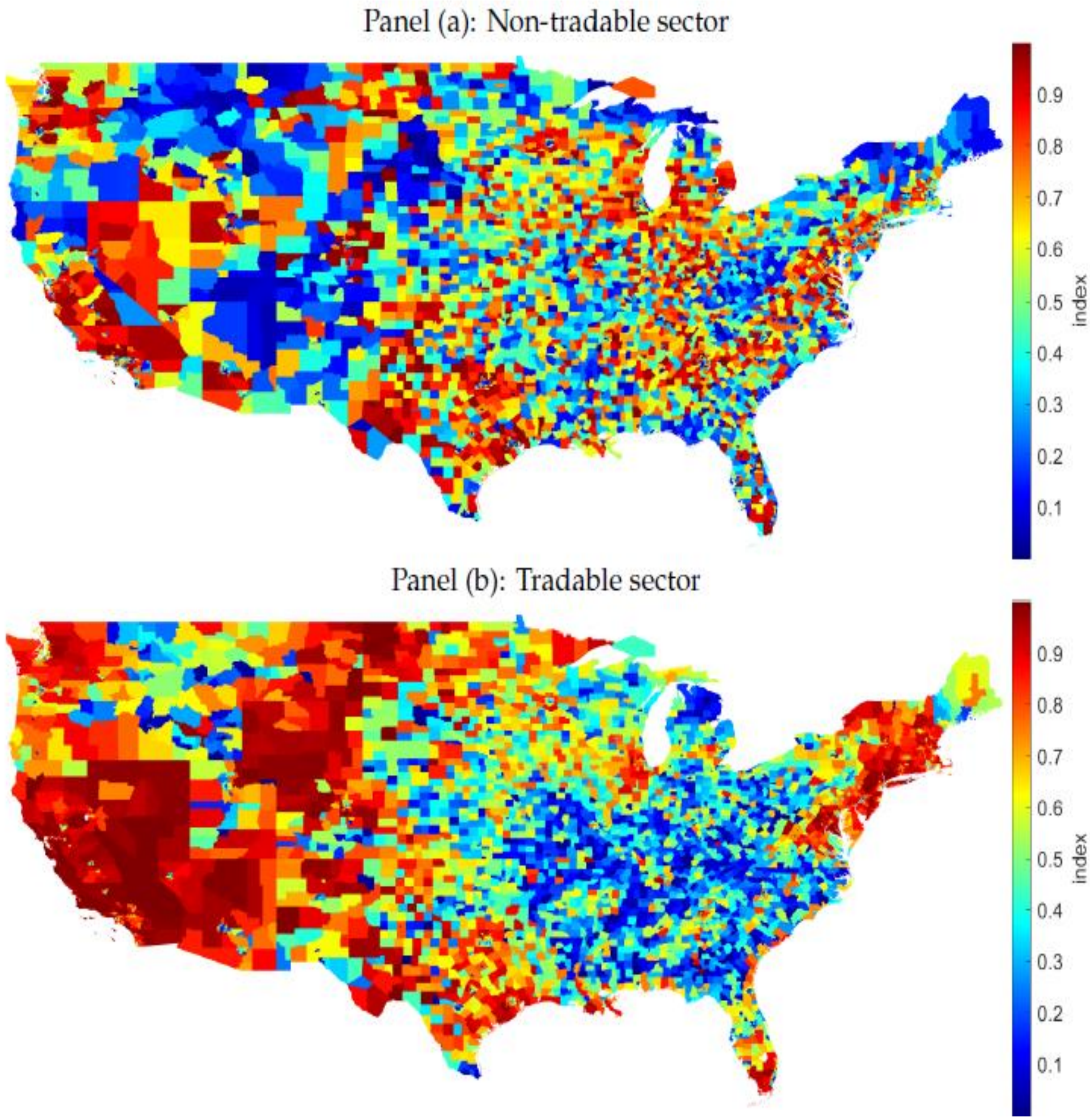

Figure J.6. Location-specific productivity, quantiles

Note: Panel (a) shows quantiles of calibrated non-tradable sector location-specific productivities, A_{Sj}. Panel (b) shows quantiles of tradable sector location-specific productivities, A_{Gj}

Table J.1. Changes in residents in 50 largest MSAs

MSA	All residents		Non-coll.	Coll.	Non-trad.	Trad.	Non-telec.	Telec.
	%	'000	'000	'000	'000	'000	'000	'000
New York-Newark-Jersey City, NY-NJ-PA	0.5	42	60	-18	-22	64	128	-86
Los Angeles-Long Beach-Anaheim, CA	-3.5	-199	-107	-92	-177	-22	136	-335
Chicago-Naperville-Elgin, IL-IN-WI	-0.4	-19	-8	-11	-45	26	104	-122
Dallas-Fort Worth-Arlington, TX	-3.1	-99	-64	-35	-93	-6	123	-222
Houston-The Woodlands-Sugar Land, TX	-3.4	-96	-67	-28	-96	1	85	-181
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	-0.1	-3	-2	-1	5	-9	-27	23
Atlanta-Sandy Springs-Alpharetta, GA	-0.4	-10	-3	-7	-34	24	50	-60
Boston-Cambridge-Newton, MA-NH	-3.2	-77	-37	-40	-57	-20	35	-111
Miami-Fort Lauderdale-Pompano Beach, FL	-5.8	-139	-87	-52	-96	-43	70	-209
San Francisco-Oakland-Berkeley, CA	-4.1	-89	-52	-37	-90	1	41	-130
Washington-Arlington-Alexandria, DC-VA-MD-WV	0.2	4	9	-5	-16	19	24	-20
Detroit-Warren-Dearborn, MI	-2.5	-47	-17	-30	-17	-29	30	-77
Phoenix-Mesa-Chandler, AZ	-5.7	-106	-73	-32	-93	-13	62	-167
Minneapolis-St. Paul-Bloomington, MN-WI	-3.8	-70	-38	-33	-32	-38	36	-106
Seattle-Tacoma-Bellevue, WA	-5.9	-102	-57	-45	-84	-18	63	-165
Riverside-San Bernardino-Ontario, CA	1.0	16	6	10	14	2	-50	66
San Diego-Chula Vista-Carlsbad, CA	-4.8	-67	-39	-28	-11	-55	-8	-58
Denver-Aurora-Lakewood, CA	-5.6	-74	-44	-30	-66	-9	52	-127
St. Louis, MO-IL	-2.0	-26	-17	-9	-21	-6	25	-51
Baltimore-Colombia-Townson, MD	-1.4	-18	-13	-4	-21	3	-12	-6
Tampa-St. Petersburg-Clearwater, FL	-4.4	-53	-39	-14	-29	-24	22	-75
Pittsburg, PA	-2.0	-22	-17	-6	-9	-14	-7	-15
Charlotte-Concord-Gastonia, NC-SC	0.5	5	5	-0	3	2	21	-16
Portland-Vancouver-Hillsboro, OR-WA	-4.9	-54	-33	-21	-29	-24	22	-75
Orlando-Kissimmee-Sanford, FL	-3.6	-38	-29	-9	-15	-23	14	-52
Cincinnati, OH-KY-IN	0.4	4	4	1	-4	8	5	-1

MSA	All residents		Non-coll.	Coll.	Non-trad.	Trad.	Non-telec.	Telec.
	%	'000	'000	'000	'000	'000	'000	'000
Kansas City, MO-KS	-2.8	-29	-15	-13	-17	-12	19	-47
Cleveland-Elyria, OH	-2.2	-22	-13	-9	-4	-18	-11	-11
San Antonio-New Braunfels, TX	-3.9	-38	-28	-10	-20	-18	-5	-33
Indianapolis-Carmel-Anderson, IN	-2.2	-21	-15	-6	-25	4	-3	-18
Columbus, OH	-1.0	-10	-3	-9	-4	-6	-0	-10
Sacramento-Roseville-Folsom, CA	-4.9	-45	-34	-11	-32	-13	-20	-25
San Jose-Sunnyvale-Santa Clara, CA	-3.5	-32	-17	-15	-29	-2	34	-65
Austin-Round Rock-Georgetown, TX	-3.6	-33	-19	-14	-18	-14	2	-34
Las Vegas-Henderson-Paradise, NV	-6.7	-59	-37	-22	-42	-17	28	-88
Nashville-Davidson-Murfreesboro-Franklin, TN	-1.8	-15	-8	-7	-18	3	3	-18
Milwaukee-Waukesha, WI	-3.9	-31	-22	-9	-21	-10	4	-35
Providence-Warwick, RI-MA	-2.9	-23	-17	-5	-22	-1	-6	-17
Virginia Beach-Norfolk-Newport News, VA-NC	-2.3	-15	-14	-0	-2	-13	-6	-9
Jacksonville, FL	-3.5	-22	-15	-6	-11	-10	10	-32
Hartford-East Hartford-Middletown, CT	-1.1	-7	-6	-1	-2	-5	-10	3
Louisville/Jefferson County, KY-IN	-0.6	-3	-3	-1	-6	3	2	-6
Memphis, TN-MS-AR	-1.8	-11	-5	-6	-1	-10	10	-20
Raleigh-Cary, NC	-4.7	-27	-16	-11	-25	-2	4	-32
Oklahoma City, OK	-6.3	-36	-25	-11	-31	-5	5	-41
Salt Lake City, UT	-7.0	-39	-23	-16	-28	-11	22	-60
Buffalo-Cheektowga, NY	-5.5	-30	-21	-9	-20	-10	4	-34
Richmond, VA	-1.0	-5	-4	-1	-1	-4	-3	-2
New Orleans-Metairie, LA	-4.9	-26	-19	-7	-22	-4	10	-36
Rochester, NY	-4.2	-22	-16	-6	-12	-9	-1	-20

Note: The table shows counterfactual results for changes in residents aggregated to the metropolitan statistical area (MSA) level for the largest 50 MSAs, ranked according to number of residents 2012-2016. The first two columns show percentage and absolute overall changes. The next two show absolute changes by education level. The next two show absolute changes by industry. The last two columns show absolute changes by occupation.

Table J.2. Changes in jobs in 50 largest MSAs

MSA	All jobs %	All jobs '000	Non-coll. '000	Coll. '000	Non-trad. '000	Trad. '000	Non-telec. '000	Telec. '000
New York-Newark-Jersey City, NY-NJ-PA	1.7	156	70	86	-21	177	123	32
Los Angeles-Long Beach-Anaheim, CA	0.3	18	16	2	-109	127	120	-102
Chicago-Naperville-Elgin, IL-IN-WI	2.7	123	87	36	-27	150	105	18
Dallas-Fort Worth-Arlington, TX	1.9	65	58	7	-57	122	126	-61
Houston-The Woodlands-Sugar Land, TX	1.3	37	37	-0	-55	92	85	-48
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	-0.8	-24	-22	-2	-7	-17	-23	-1
Atlanta-Sandy Springs-Alpharetta, GA	2.7	68	51	17	-14	82	51	17
Boston-Cambridge-Newton, MA-NH	-1.0	-27	-15	-13	-42	15	35	-63
Miami-Fort Lauderdale-Pompano Beach, FL	-4.6	-113	-80	-34	-97	-16	66	-179
San Francisco-Oakland-Berkeley, CA	1.4	33	25	8	-36	69	31	2
Washington-Arlington-Alexandria, DC-VA-MD-WV	2.9	63	37	26	11	51	24	39
Detroit-Warren-Dearborn, MI	-2.3	-44	-28	-16	-36	-9	27	-72
Phoenix-Mesa-Chandler, AZ	-2.5	-47	-25	-23	-61	13	59	-107
Minneapolis-St. Paul-Bloomington, MN-WI	-4.5	-84	-49	-36	-54	-30	38	-123
Seattle-Tacoma-Bellevue, WA	-2.3	-43	-20	-23	-56	14	65	-108
Riverside-San Bernardino-Ontario, CA	-7.0	-93	-74	-19	-23	-70	-36	-57
San Diego-Chula Vista-Carlsbad, CA	-12.5	-169	-111	-58	-48	-121	-9	-160
Denver-Aurora-Lakewood, CA	-1.6	-23	-8	-15	-45	23	51	-74
St. Louis, MO-IL	-1.5	-20	-12	-8	-21	1	24	-44
Baltimore-Colombia-Townson, MD	-0.5	-6	-6	-1	-10	3	-10	4
Tampa-St. Petersburg-Clearwater, FL	-4.1	-52	-34	-17	-38	-14	20	-72
Pittsburg, PA	-2.1	-24	-18	-7	-10	-14	-6	-19
Charlotte-Concord-Gastonia, NC-SC	2.6	30	22	7	-5	34	22	7
Portland-Vancouver-Hillsboro, OR-WA	-5.6	-63	-38	-25	-35	-28	24	-87
Orlando-Kissimmee-Sanford, FL	-5.2	-61	-44	-17	-27	-34	16	-77
Cincinnati, OH-KY-IN	1.5	15	11	4	-3	18	9	6
Kansas City, MO-KS	-3.2	-33	-21	-12	-25	-8	19	-52

MSA	All jobs %	All jobs '000	Non-coll. '000	Coll. '000	Non-trad. '000	Trad. '000	Non-telec. '000	Telec. '000
Cleveland-Elyria, OH	-3.5	-37	-26	-11	-17	-20	-7	-30
San Antonio-New Braunfels, TX	-8.6	-81	-63	-18	-26	-55	-5	-76
Indianapolis-Carmel-Anderson, IN	3.1	31	23	9	-1	33	-2	34
Columbus, OH	-0.4	-4	-2	-2	-6	2	2	-6
Sacramento-Roseville-Folsom, CA	-6.9	-63	-41	-22	-22	-41	-17	-46
San Jose-Sunnyvale-Santa Clara, CA	0.8	8	8	-1	-19	26	37	-29
Austin-Round Rock-Georgetown, TX	-6.5	-61	-41	-20	-14	-47	-1	-61
Las Vegas-Henderson-Paradise, NV	-7.9	-7.2	-49	-22	-42	-29	27	-98
Nashville-Davidson-Murfreesboro-Franklin, TN	0.7	6	6	0	-6	12	3	3
Milwaukee-Waukesha, WI	-1.5	-13	-9	-4	-17	4	8	-22
Providence-Warwick, RI-MA	-2.8	-20	-14	-6	-16	-3	-10	-10
Virginia Beach-Norfolk-Newport News, VA-NC	-5.4	-35	-26	-10	-12	-23	-7	-28
Jacksonville, FL	-3.1	-20	-13	-7	-16	-4	10	-30
Hartford-East Hartford-Middletown, CT	-2.4	-15	-11	-4	-5	-10	-8	-7
Louisville/Jefferson County, KY-IN	2.5	16	12	4	-3	19	2	14
Memphis, TN-MS-AR	-1.6	-10	-7	-3	-12	2	10	-20
Raleigh-Cary, NC	-1.3	-8	-4	-4	-7	-2	6	-14
Oklahoma City, OK	-2.3	-14	-9	-5	-17	3	6	-20
Salt Lake City, UT	-4.2	-28	-15	-13	-25	-2	28	-56
Buffalo-Cheektowga, NY	-4.5	-26	-18	-8	-18	-8	3	-29
Richmond, VA	-1.5	-9	-6	-3	-6	-3	-2	-7
New Orleans-Metairie, LA	-1.2	-7	-4	-3	-15	8	13	-19
Rochester, NY	-3.9	-20	-14	-7	-11	-9	-1	-19

Note: The table shows counterfactual results for changes in jobs aggregated to the metropolitan statistical area (MSA) level for the largest 50 MSAs, ranked according to number of residents 2012-2016. The first two columns show percentage and absolute overall changes. The next two show absolute changes by education level. The next two show absolute changes by industry. The last two columns show absolute changes by occupation.